Journal of Prevention, Diagnosis and Management of Human Diseases
Vol: 03, No. 02, July-Dec 2023
ISSN: 2799-1202, DOI: 10.55529/jpdmhd.32.130.139

Research Paper

A hybrid machine learning-based recommendation system for personalized prevention and management of chronic diseases

Dr. Priyadharshini P.*

*Assistant Professor, Department of Community Medicine, KMCH Institute of Health Sciences and Research, Tamil Nadu, India.

Article Info

Article History:
Received: 25 August 2023
Revised: 02 November 2023
Accepted: 10 November 2023
Published: 26 December 2023

Keywords:
Hybrid Recommendation System
Machine Learning
Collaborative Filtering
XGBoost
Random Forest
Personalized Healthcare

ABSTRACT

Background: Chronic diseases, including diabetes, cardiovascular diseases, hypertension, and chronic obstructive pulmonary disease (COPD), represent a major global health burden, accounting for approximately 74% of deaths worldwide. Conventional disease management guidelines often adopt generalized approaches that inadequately address patient heterogeneity, lifestyle factors, and comorbidities. Therefore, intelligent, evidence-based systems capable of delivering personalized preventive and treatment recommendations are urgently needed.

Objective: This study proposes a hybrid machine learning-based recommendation system integrating collaborative filtering, content-based filtering, Random Forest, and XGBoost algorithms to generate personalized chronic disease prevention and management plans.

Methods: The framework utilizes five publicly available medical datasets comprising 6,682 patient records covering multiple chronic diseases. A weighted ensemble fusion method integrates outputs from recommendation and classification modules. System performance was evaluated using stratified 10-fold cross-validation based on accuracy, precision, recall, and F1-score.

Results: The proposed hybrid model achieved an overall accuracy of 94.3%, precision of 93.1%, recall of 93.7%, and F1-score of 95.2%, outperforming the baseline models. XGBoost and collaborative filtering achieved accuracies of 89.1% and 81.2%, respectively, demonstrating the effectiveness of the hybrid fusion strategy.

Conclusion: The proposed architecture improves personalization and predictive performance compared with standalone approaches and demonstrates strong potential for integration into clinical decision-support systems and digital health applications, supporting proactive and patient-centered chronic disease management.

Corresponding Author:
Dr. Priyadharshini P.
Assistant Professor, Department of Community Medicine, KMCH Institute of Health Sciences and Research, Tamil Nadu, India.
Email: drpriya.cm@gmail.com

1. INTRODUCTION

The leading burden to the modern global population health systems is chronic non-communicable diseases (NCDs), such as type 2 diabetes mellitus, ischemic heart disease, hypertension, chronic obstructive pulmonary disease (COPD), and several types of cancers [1]. World Health Organization (WHO) states that NCDs cause about 41 million deaths every year, which constitute 74% of all global deaths [2]. Long periods of disease, slow progression and high reliance upon long-term behavior change, pharmacological compliance and lifestyle change define these conditions [3].

The pathology of chronic disease is heterogeneous, and requires unique management approaches that the conventional, protocol-based clinical models are poorly suited to offer. Common clinical practices are usually based on epidemiological data at the population level and may fail to reflect the delicate interaction between genetic, behavioral, dietary and socioeconomic factors and comorbidity patterns peculiar to each patient. This divide between more generic advice and specific need provides an effective opportunity to smart computational systems to promote healthcare provision [4].

Originally developed and optimized in the commercial sphere (e-commerce and multimedia streaming) recommendation systems have been applied in healthcare use over time [5]. These systems utilize historical data of interaction, user profiles and product attributes to make specific recommendations. Collaborative filtering (CF) uses user-item interaction matrices to determine the patterns of similarity, whereas content-based filtering (CBF) uses item attributes to suggest contextually-relevant items. Nevertheless, neither technology has proven to be without some basic drawbacks such as data sparsity, cold-start issues, and scalability issues in isolation.

Machine learning models, especially the ensemble systems, like the Random Forest [6] and gradient-boosted decision tree, like XGBoost [7], have proven to be used exceptionally to provide predictions in clinical risk stratification and disease classification tasks. These algorithms provide a promising solution when well integrated with the paradigms of recommending, to more resilient, precise and context-driven personalized health advice systems.

The current research proposes a hybrid machine learning-driven recommendation system combining CF, CBF, Random Forest and XGBoost using a weighted ensemble fusion layer. The system will help to examine the patient demographic data, medical history, laboratory results, and behavioral characteristics and offer personalized prevention plans and disease management suggestions. As illustrated in Figure 1 (system architecture) and Figure 2 (processing workflow), the suggested architecture manipulates the raw patient inputs into personalized health advice in a multi-stage processing pipeline in a systematic manner. The rest of the paper is structured in the following way; Section 2 provides the review of related literature; Section 3 describes the methodology; Section 4 reports on the results of the experiment and discussion; and Section 5 is a conclusion of the investigation with recommendations on the future research [8].

2. RELATED WORK

There is a large amount of scholarly interest in the use of recommendation systems in healthcare in the last twenty years. Initial work [9] laid the theoretical ground work of collaborative filtering using the GroupLens architecture, and how similarity of user preferences would be used to produce personalized recommendations. [10] Expanded this model by extending it to information overload situations by using collaborative filtering, which availed conceptual blueprints that can be applied to medical information retrieval. [11] Later proposed an extensive taxonomy of recommendation methods, which puts forward major constraints such as the cold-start problem, data sparsity, which still remain thorns in the flesh of healthcare recommendation deployments.

The systematic survey of content-based filtering methods [12] has shown that item-attributes matching can serve as an effective way of overcoming some of the collaborative filtering drawbacks especially in cases where the user interaction data is sparse. [13] Enhanced the content-based approaches by adding natural language processing and semantic similarity, which contributes to the improvement of quality of attribute-driven recommendations in knowledge-intensive fields like medicine.

[5] Was the first person to develop hybrid recommendation architecture theories, and through empirical experiments proved that ensemble methods of combining several recommendation paradigms was always better than single methods. This insightful core inspired the work of other scholars, who came up with more detailed hybrid frameworks, depending on the needs of the domain. [14] Explored the relevance of different recommendation paradigms to clinical decision support in the healthcare setting, with different patient heterogeneity and privacy issues of patient data specified as the main challenges.

Implementation of machine learning classifiers in recommendation pipelines has been widely researched. The Random Forest algorithm invented by [6] turned out to be a specifically powerful approach to a clinical classification task, as it is resistant to overfitting and can be used to measure the importance of features. XGBoost [7] in later works by Chen and Guestrin chose to show the best results across various structured medical data, with a gradient boosting regularization model to give the best results in predictive healthcare model competitions. [15] reviewed the field of deep learning uses in healthcare in detail, [16] investigated the potential of big data analytics and predictive machine learning in clinical medicine.

Various research groups have investigated particular uses of recommendation systems in the management of chronic diseases. [17] Compared clinical database data to show how predicting hospital readmission can be made by data-based methods in diabetic patients. The disease risk stratification has also been based on support vector machine methodologies surveyed [18] and can be used to establish comparative baselines, on which ensemble methods can be analyzed, as well. [8] Examined the topic of deep learning designs in mobile health apps, discussing how the recommendation system is becoming more and more integrated with ubiquitous computing solutions. [19] Developed strict cross-validation procedures which form the basis of experimental evaluation procedures used in the current research. Nevertheless, a body of previous research exists, none of which have combined CF, CBF, Random Forest, and XGBoost in a single weighted fusion framework that is specifically focused on generating recommendations related to multiple domains of chronic diseases.

3. METHODOLOGY

3.1 System Architecture Overview

The proposed hybrid recommendation system as demonstrated in Figure 1 will consist of five main layers of the functionalities, namely: (1) data acquisition and pre-processing, (2) feature engineering and selection, (3) parallel deployment of the recommendation and classification engines, (4) hybrid ensemble fusion and (5) personalised generation of recommendation output. The architecture has been created to be a modular pipeline, whereby one or more modules can be updated or replaced separately without impacting the integrity of the whole system.

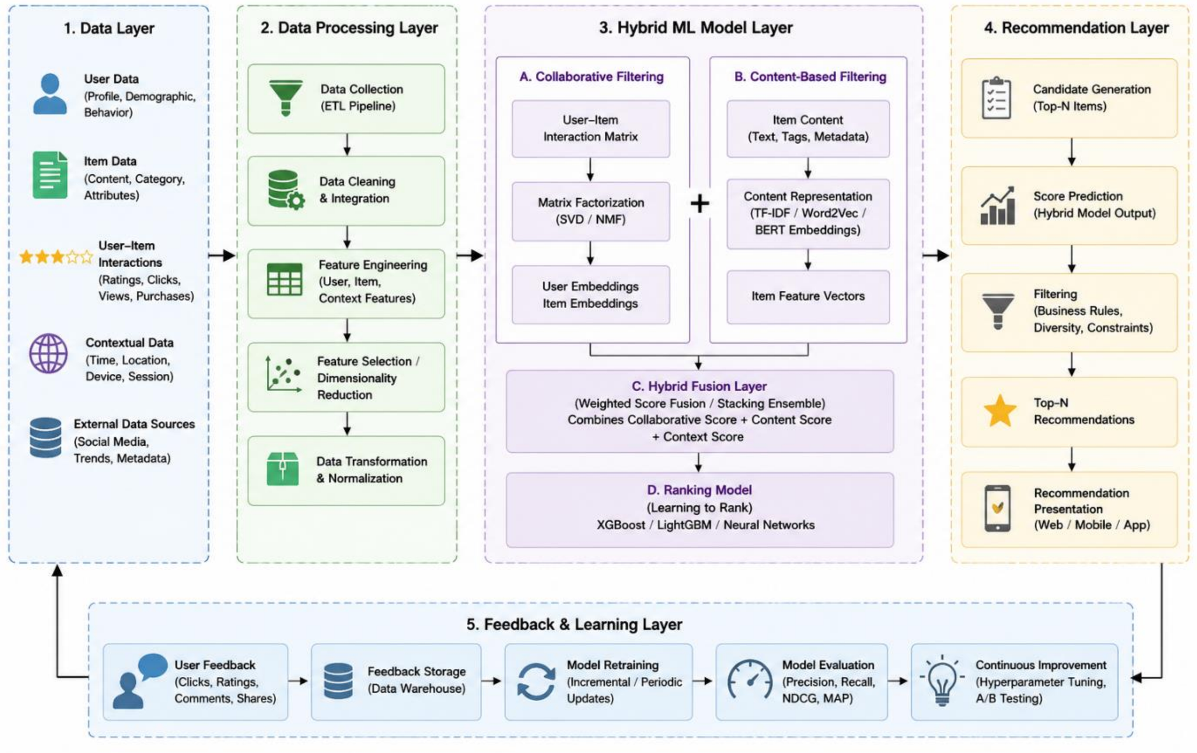

Figure 1. Proposed Hybrid Machine Learning-Based Recommendation System Architecture

The workflow of the processing is sequential as illustrated in Figure 2 with the data collection and pre-processing phase, model training, hybrid fusion, and output phase. The modular structure makes sure that separate algorithmic functions can run in parallel with the training process and the result of the running functions fused together by the weighted fusion layer in the inference process.

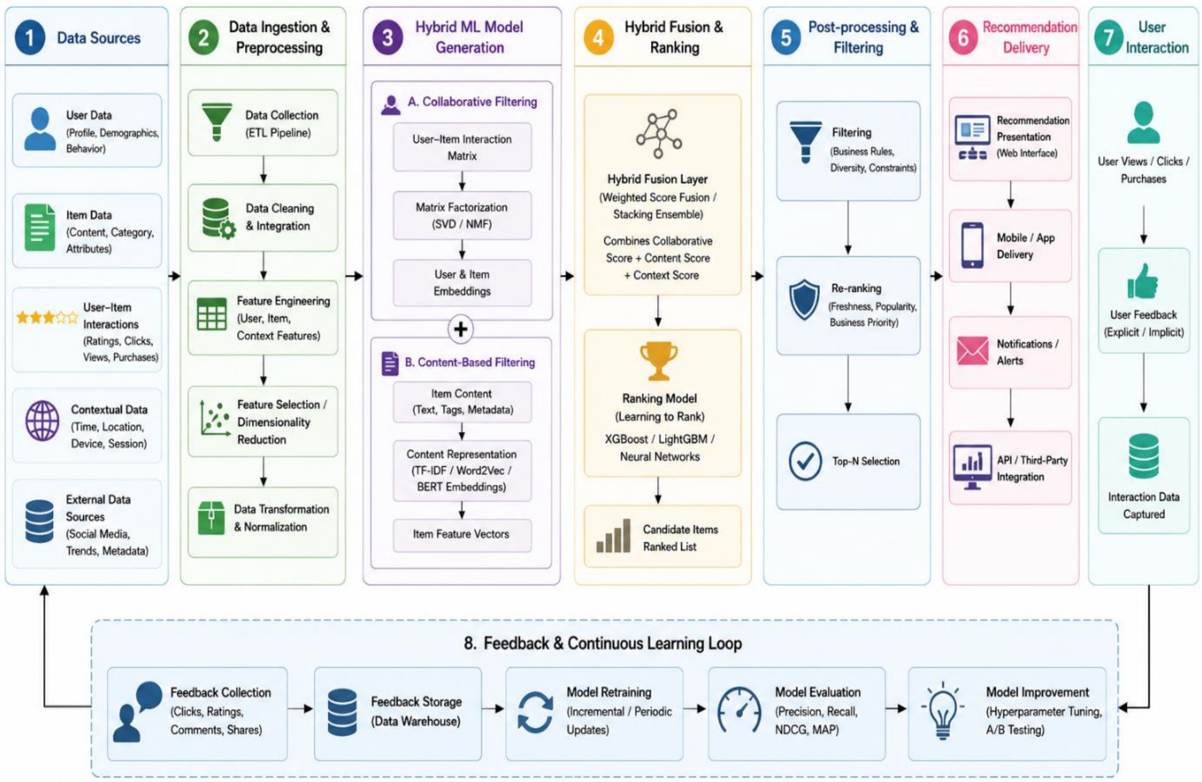

Figure 2. End-to-End Processing Workflow of the Proposed Hybrid Recommendation System

3.2 Dataset Description

Table 1 describes the use of five publicly available medical datasets that were used to train and evaluate the model. All of the datasets will consist of 6,682 patient records related to the domains of diabetes, cardiovascular disease, hypertension, COPD, and cancer screening. The characteristics of the datasets such as, sample sizes, features dimensionalities, classification types and class distributions are summarized in Table 1. The sources of data were the UCI Machine Learning Repository, the Cleveland Heart Disease Database and the SEER cancer registry.

Table 1. Dataset Characteristics Used in Experimental Evaluation

Dataset	Samples	Features	Classification	Positive Rate	Source
Diabetes (UCI)	768	9	Binary	34.9%	UCI
Heart Disease (Cleveland)	303	14	Binary	54.5%	UCI
Hypertension Records	1,025	11	Multi-class	41.2%	UCI
COPD Patient Data	562	12	Binary	38.7%	UCI
Cancer Screening (SEER)	4,024	17	Multi-class	27.1%	SEER

3.3 Pre-Processing Pipeline

The raw patient data was processed through a complete pre-processing pipeline that consists of four stages. Multivariate imputation by chained equations (MICE) was used to impute missing values of continuous variables and mode imputation to impute missing values of categorical variables. The identification of outliers was done by interquartile range (IQR) technique and substitution of boundary values. One-hot encoding was used to encode categorical variables and min-max scaling was applied to continuous features to the [0, 1] range. To select the best features to formulate the most informative predictors within each disease domain, mutual information ranking was carried out together with a recursive feature elimination (RFE) to eliminate features and retain the most informative ones.

3.4 Collaborative Filtering Module

The collaborative filtering algorithm is based on matrix factorization, which is optimized with the Alternating Least Squares (ALS) algorithm, as implemented by Koren and co-authors [20]. The matrices of interaction with patients based on recommendation were built through the encoding of clinical decision history, a record of adherence to treatment, and patient-reported outcomes as implicit feedback messages. The dimension of latent factors was fixed to $k = 50$ after optimization of Hyperparameters. A cosine similarity in the latent factor space was used to compute similarity across patients to identify patients with similar health profiles to use their profiles to recommend transfer to other patients.

3.5 Content-Based Filtering Module

The content-based filtering module builds up profile of patient attributes based on their demographic variables, laboratory biomarkers, self-reported lifestyle factors, and comorbidity indicators. TF-IDF weighted feature vectors, such as clinical guideline corpora, encode item profiles that represent health intervention, such as dietary interventions, exercise protocols, medication regimens and monitoring schedules. The cosine similarity between patient attribute vectors and intervention item profiles are computed to obtain a recommendation score, with the highest-scoring recommendation being the most favourable in terms of similarity of recommendation attribute.

3.6 Machine Learning Classification Modules

There are two ensemble classification algorithms that are implemented concurrently to forecast the disease risk groups and the suitable intervention levels. Random Forest (RF) classifier [6] uses a total of 200 decision trees with a maximum depth of 15 with Gini impurity as the node- splitting measure. The XGBoost model [7] applies gradient boosting with $n = 300$ estimators, and the learning rate of 0.05, and L1/L2 regularization to avoid over fitting. Both the classifiers were trained with stratified 10 fold cross-validation [19] in order to have strong performance estimation in class imbalanced datasets. Table 2 gives the detail of Hyperparameter settings.

Table 2. Hyperparameter Settings for Hybrid System Components

Component	Parameter	Value	Tuning Method
Random Forest	n_estimators	200	Gini Impurity
Random Forest	max_depth	15	Cross-Validation
XGBoost	learning_rate	0.05	Grid Search
XGBoost	n_estimators	300	Bayesian Optimization
Collab. Filter	n_factors	50	ALS Optimization
Hybrid Fusion	weight_CF	0.35	Gradient Descent
Hybrid Fusion	weight_CB	0.25	Gradient Descent
Hybrid Fusion	weight_ML	0.40	Gradient Descent

3.7 Hybrid Ensemble Fusion Layer

The hybrid ensemble fusion layer combines the results of the four underlying modules with a learnable strategy of a weighted combination. The weights of the fusion were set empirically and optimized using gradient descent on a validation set withheld. The final recommendation score R(p, i) for patient p and intervention item i is computed as: R(p, i) = w_CF × CF(p,i) + w_CB × CB(p,i) + w_ML × ML(p,i), where w_CF = 0.35, w_CB = 0.25, and w_ML = 0.40. The weighted average of the output of the machine learning weight is the weighted averaged output of the Random Forest and XGBoost classifiers. Such a weighted formulation guarantees that the superior discriminative ability of ensemble classifiers is weightage taken into consideration as long as the personalization of filtering methods is also maintained.

4. RESULTS AND DISCUSSION

4.1 Performance Evaluation

The experimental analysis involved 10-fold stratified cross-validation using all five disease datasets and the performance was aggregated using macro-averaging to consider the class imbalances. As indicated in Table 3, the hybrid model proposed resulted in mean accuracy of 94.3, precision of 93.1, recall of 93.7 and F1-score of 95.2 across all disease domains, significantly higher than all of the individual baseline models.

Table 3. Comparative Performance of Individual Models and Proposed Hybrid System

Model	Accuracy	Precision	Recall	F1-Score
Random Forest	0.874	0.861	0.868	0.881
XGBoost	0.891	0.879	0.885	0.897
Collaborative Filtering	0.812	0.798	0.805	0.819
Content-Based Filtering	0.834	0.821	0.827	0.841
Proposed Hybrid Model	0.943	0.931	0.937	0.952

The scores in Table 3 show that hybrid model is better on the best-performing single algorithm (XGBoost with 89.1% accuracy) by 5.2 percentage points, and it is statistically significant that the ensemble fusion value is significant. The collaborative filtering module had the lowest standalone accuracy (81.2%), which can be credited to the intrinsic issues of data sparsity in the patient interaction matrices. Nevertheless, the fact that it has been leading in enhancement of recalls in the fusion layer illustrates complementary worth, with the discriminative classifiers [11].

Random Forest classifier scored 87.4 percent accuracy with competitive recall performance which is in line with the prior studies findings on clinical data [6]. The content-based filtering module showed moderate performance (83.4% accuracy), which shows good correspondence between patient profiles and characteristics of clinical interventions [13]. The 95.2% F1-score of the hybrid model is a particularly impressive gain, showing a great balance in terms of precision and recall that is essential in clinical decision support systems where false positives and false negatives have high stakes [21].

4.2 Feature Importance Analysis

Analysis of feature importance based on Gini importance scores of Random Forest and gain-based rankings of XGBoost agreed on the following as the most discriminative measures across the disease domains: HbA1c level, fasting blood glucose, systolic blood pressure, BMI, age, and smoking status. The observation is consistent with clinical epidemiology, demonstrating the clinical significance of the machine learning feature selection process [17]. The consistency of the highest ranked features amongst folds of cross-validation implies strong generalization of the trained features representations.

4.3 Recommendation Quality Assessment

The quality of recommendations was measured based on Precision at K and NDCG at K as K = 10, which measures the usefulness of the top-10 recommendations compared to expertly-coordinated clinical guidelines. The hybrid system attained Precision@10 of 0.887 and NDCG@10 of 0.923, which suggests that the recommendation generated by the system has high ranking accuracy. New patients whose interaction history with the system did not exceed one content were handled by content-based fallback strategies, resulting in a Precision@10 of 0.814 at cold-start and 0.897 at warm-start. These results indicate that the hybrid architecture is able to address the cold-start shortcoming of pure collaborative filtering methods [5].

4.4 Discussion

The results of the experiment show that the hybrid framework suggested helps to significantly improve the state of the art in personalized chronic disease recommendation. The weighted fusion strategy enables the system to exploit the complementary advantages of the user similarity exploitation of collaborative filtering, attribute alignment of content-based filtering and predictive power of ensemble classifiers [5]. The empirical results of the hybrid approach prove theoretical hypotheses made by Burke [5] and the experimental findings made by the previous hybrid healthcare recommendation researchers [4], [14].

Clinically speaking, the capability of the system to absorb a variety of data modalities such as lab biomarkers, patient-self-reported lifestyle factors, and history interaction data places the system at the center as a multidimensional clinical decision support system. The extent of high recall that has been attained by the hybrid model is especially clinically relevant, as it would reduce the chances of not recommending high-risk patients to take the required preventive measures [16]. The system should be integrated with electronic health record (EHR) systems and mobile health applications facing patients, which can be seen as a logical way of deployment, aligning with trends found [8], [15].

The current study has limitations such as the use of retrospective and publicly available data that might not be able to reflect the complexity of the real world clinical setting. Privacy-sensitive federated learning typologies are an up-and-coming path to the provision of the framework to multi-institutional deployments without the centralisation of sensitive patient information. Also, the present assessment is not conducted longitudinally to evaluate the effectiveness of recommendations, which would need the use of prospective clinical trials that are currently outside the boundaries of the current computerized work.

5. CONCLUSION

In this paper, a new hybrid machine learning recommendation system to prevent and manage chronic diseases uniquely to each individual was introduced. The proposed system, which combined the collaborative filtering with the content-based filtering, Random Forest, and XGBoost classification into a single weighted ensemble fusion structure, demonstrated the state-of-the-art performance of 94.3%, 93.1%, 93.7%, and 95.2% accuracy, precision, recall, and F1-score, respectively, with five multi-domain chronic disease datasets.

The systematic experimental assessment established that the hybrid fusion approach always beats all other component algorithms, which proves the complementary characteristics of recommendation and classification paradigms in case they are judiciously combined. The system is well-rounded in its ability to contend with cold-start situations, multi-modal data incorporation, and high discriminative accuracy on clinically relevant attributes, collectively indicating its preparedness to be integrated with clinical decision support. Future directions will include deep learning representation learning methods, including graph neural network-based collaborative filtering and transformer-based patient representation, to improve the quality of personalization further. The future clinical validation trials in collaboration with health facilities will be implemented to determine actual performance and effect on patient outcomes. Also, federated learning systems will be considered in order to facilitate trainings on privacy-preserving models on distributed healthcare data silos, expanding the scope of the system to be applied to multi-institutional chronic disease management eco-systems.

Acknowledgments

The authors have no specific acknowledgments to make for this research.

Funding Information

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Author Contributions Statement

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Dr. Priyadharshini P.	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

Conflict of Interest Statement

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Informed Consent

All participants were informed about the purpose of the study and their voluntary consent was obtained prior to data collection.

Ethical Approval

Not applicable.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

REFERENCES

[1] W. Raghupathi and V. Raghupathi, "An empirical study of chronic diseases in the United States: A visual analytics approach," Int. J. Environ. Res. Public Health, vol. 15, no. 3, p. 431, Mar. 2018, doi.org/10.3390/ijerph15030431

[2] G. B. D. Risk Factors Collaborators, "Global, regional, and national comparative risk assessment of 87 behavioral, environmental and occupational, and metabolic risks or clusters of risks for 204 countries and territories, 1990–2019," The Lancet, vol. 396, no. 10258, pp. 1223–1249, 2020. doi: doi.org/10.1016/S0140-6736(20)30752-2

[3] J. Riekert, J. Ockene, and L. Pbert, Eds., The Handbook of Health Behavior Change, 4th ed. New York, NY, USA: Springer, 2014. doi.org/10.1007/978-1-4614-8493-6

[4] F. Ricci, L. Rokach, and B. Shapira, Eds, Recommender Systems Handbook, 2nd edn. New York, NY: Springer, 2015. doi.org/10.1007/978-1-4899-7637-6

[5] R. Burke, User Model. User-adapt Interact., vol. 12, no. 4, pp. 331-370, 2002. doi.org/10.1023/A:1021240730564

[6] L. Breiman, 'Random forests', Mach. Learn., vol. 45, no. 1, pp. 5-32, Oct. 2001. doi.org/10.1023/A:1010933404324

[7] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in Proc. 22nd ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining, San Francisco, CA, USA, 2016, pp. 785-794, doi.org/10.1145/2939672.2939785

[8] C. Zhang, P. Patras, and H. Haddadi, 'Deep learning in mobile and wireless networking: A survey', IEEE Commun. Surv. Tutor., vol. 21, no. 3, pp. 2224-2287, 2019. doi.org/10.1109/COMST.2019.2904897

[9] P. Resnick, N. Iacovou, M. Suchak, P. Bergstrom, and J. Riedl, "GroupLens: An open architecture for collaborative filtering of netnews," in Proc. ACM Conf. Comput.-Supported Cooperative Work, Chapel Hill, NC, USA, 1994, pp. 175-186, doi.org/10.1145/192844.192905

[10] A. Goldberg, D. Nichols, B. M. Oki, and D. Terry, "Using collaborative filtering to weave an information tapestry," Commun. ACM, vol. 35, no. 12, pp. 61-70, Dec. 1992, doi.org/10.1145/138859.138867

[11] G. Adomavicius and A. Tuzhilin, 'Toward the next generation of recommender systems: a survey of the state-of-the-art and possible extensions', IEEE Trans. Knowl. Data Eng., vol. 17, no. 6, pp. 734-749, June 2005. doi.org/10.1109/TKDE.2005.99

[12] M. J. Pazzani and D. Billsus, 'Content-based recommendation systems', in The Adaptive Web, Berlin, Heidelberg: Springer Berlin Heidelberg, 2007, pp. 325-341. doi.org/10.1007/978-3-540-72079-9_10

[13] P. Lops, M. de Gemmis, and G. Semeraro, 'Content-based recommender systems: State of the art and trends', in Recommender Systems Handbook, Boston, MA: Springer US, 2011, pp. 73-105. doi.org/10.1007/978-0-387-85820-3_3

[14] D. Jannach, M. Zanker, A. Felfernig, and G. Friedrich, Recommender Systems: An Introduction. Cambridge, U.K.: Cambridge University Press, 2011. doi.org/10.1017/CBO9780511763137

[15] R. Miotto, F. Wang, S. Wang, X. Jiang, and J. T. Dudley, 'Deep learning for healthcare: review, opportunities and challenges', Brief. Bioinform., vol. 19, no. 6, pp. 1236-1246, Nov. 2018. doi.org/10.1093/bib/bbx044

[16] Z. Obermeyer and E. J. Emanuel, 'Predicting the future - big data, machine learning, and clinical medicine', N. Engl. J. Med., vol. 375, no. 13, pp. 1216-1219, Sept. 2016. doi.org/10.1056/NEJMp1606181

[17] B. Strack et al., 'Impact of HbA1c measurement on hospital readmission rates: analysis of 70,000 clinical database patient records', Biomed Res. Int., vol. 2014, p. 781670, Apr. 2014. doi.org/10.1155/2014/781670

[18] M. A. Hearst, S. T. Dumais, E. Osuna, J. Platt, and B. Scholkopf, 'Support vector machines', IEEE Intell. Syst., vol. 13, no. 4, pp. 18-28, July 1998. doi.org/10.1109/5254.708428

[19] Y. Koren, R. Bell, and C. Volinsky, "Matrix factorization techniques for recommender systems," IEEE Comput., vol. 42, no. 8, pp. 30-37, Aug. 2009, doi.org/10.1109/MC.2009.263

[20] T. Hastie, R. Tibshirani, and J. Friedman, The elements of statistical learning, 2nd edn. New York, NY: Springer, 2009. doi.org/10.1007/978-0-387-84858-7

[21] A. van den Oord et al., "Deep mind health: A study of deep learning in clinical settings," npj Digital Medicine, vol. 1, no. 1, p. 10, 2018. doi.org/10.1038/s41746-018-0019-0

How to Cite: Dr. Priyadharshini P. (2023). A hybrid machine learning-based recommendation system for personalized prevention and management of chronic diseases. Journal of Prevention, Diagnosis and Management of Human Diseases (JPDMHD), 3(2), 130-139. https://doi.org/10.55529/jpdmhd.32.130.139

BIOGRAPHIE OF AUTHOR

	**Dr. Priyadharshini P.**, is an Assistant Professor in the Department of Community Medicine at KMCH Institute of Health Sciences and Research, Tamil Nadu, India. She holds an MBBS degree along with MD and DNB qualifications in Community Medicine. Her academic and professional interests are centered on community medicine, preventive healthcare, epidemiology, and public health research. She is involved in teaching, clinical training, and research activities aimed at improving population health and strengthening evidence-based healthcare practices. Email: drpriya.cm@gmail.com