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Health Recommender System for Cervical Cancer Prognosis in Women

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***Abstract*—The large amount of digital data of patients are available for health domain to be used successfully for extracting information and aid disease prediction. Therefore, the available digital information for patient-oriented decision-making substantially expanded. Recommender systems may offer more laymen-friendly knowledge to patients in this sense, helping to better understand their clinical status as reflected by their reports. Health Recommender Systems (HRSs) are a viable solution when it comes to offering resources to support clinicians in the diagnosis of illnesses, as well as supporting people with guidance on how to preserve their health. This study has proposed a Health Recommender System using a feature selection method based on the Multi Objective Genetic Algorithm (MOGA) to help women by providing information on the features responsible for prognosis of Cervical Cancer in women. It also recommends some prediction models for Cervical Cancer prediction with high accuracy. It has used Cervical Cancer Risk Classification dataset for implementation and accuracy as the evaluation parameter.**

***Index Terms*—Health Recommender System, Multi Objective Genetic Algorithm, Feature Selection, Prediction Accuracy**

I. Introduction

Recommender systems (RSs) provide services to the users by analyzing their past data. They have proven their efficiency in all most all domains. Recommender systems have left out tremendous remarks in the domains like e-commerce and social networks. Healthcare is an important domain which also demands efficient recommender systems to be designed to make the users aware by predicting the diseases according to their current life style activities and Fig. 1 represents a framework of a RS for health domain. Cancer is one of the diseases known to be the second leading cause of death in the world of all diseases. Cancer is a serious condition that can develop anywhere in the body. Cervical cancer is one of the most significant causes of death for women worldwide and ranks fourth among all cancers. Cervical Cancer is the uncontrolled development of the lining of the cervix (part of the female reproductive system) by abnormal cells. In 42 countries, it is a leading cause of cancer deaths in women. Anticipating the onset of this cancer, therefore, plays an inevitable role in saving the lives of women [1]. Disease prediction is a classification task with prone to disease and not prone to disease as the two class values. Feature selection in classification tasks is a significant pre-processing stage [2]. The feature selection seeks to minimise both the error rate of classification and the number of features, which are typically two conflicting objectives. In this regard, the proposed recommender system has used Multi Objective Genetic Algorithm (MOGA) based feature selection approach to find out the most promising features responsible for the cause of Cervical Cancer in women with high prediction accuracy. It has also tried to recommend prediction models for accurate prediction of this disease.

The remainder of the article is arranged as follows. In the next section some papers related to recommender system with multi-objective concepts have been surveyed. The methodology of the proposed system is defined in Section 3. The experimental results are illustrated in section 4, and in section 5 the conclusion and future work are represented.

II. Literature Survey

Recommender Systems are the software solutions having the capability to infer knowledge according to the information hidden in the data of the user. Formally RS can be defined as

$$F : U \times I \rightarrow R_N \tag{1}$$

Where R_N represents the top-N recommended items for the user $u \in U$ and for an item $I_u \in I$ by the utility function F which is responsible to produce R_N which maximizes the utility values for user u to the item I_u. This is known as top-N recommendation problem. RS can also be defined as prediction problem in which it is predicted that whether a specific item is meant for the user or not. Various health recommender systems (HRSs) have been proposed to address top-N recommendation and prediction. In [3], a survey on HRS has been proposed that explored different HRS approaches and assessment methods with implementation. The drug response prediction was proposed as an RS problem in [4], and a collaborative filtering

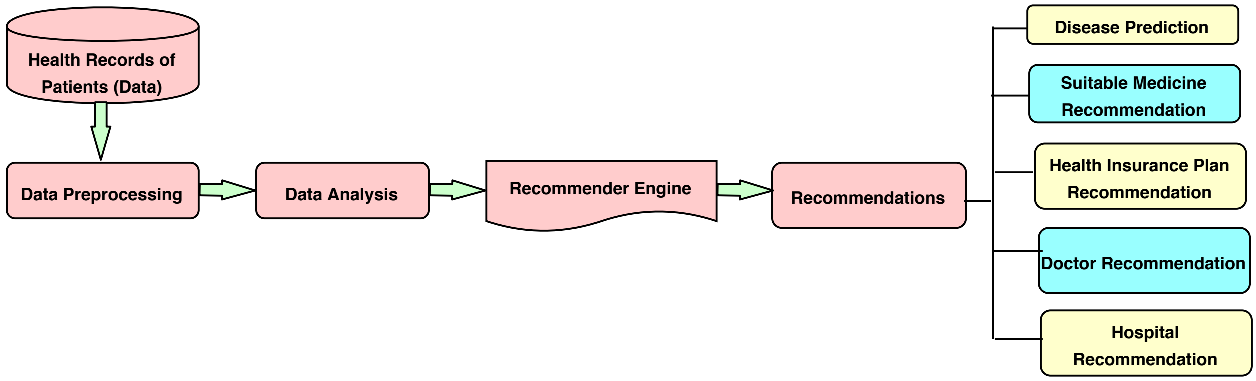

Fig. 1. Health Recommender System

approach was developed to estimate cell line anti-cancer drug responses by combining cell line similarity networks and drug similarity networks based on the fact that similar cell lines and similar drugs have similar responses.In [5], a RS is proposed which predicts cancer drug reactions to unseen cell-lines/patients based on drug and cell-line learning projections into a latent harmacogenomic space. A HRS using deep neural network and restricted boltzman machine has been proposed in [6] which provides insight into how HRS can effectively use big data analytic. In [7], a RS has been proposed to suggest a set of to-avoid drugs for a prescription that, if taken along with the prescription, would cause adverse drug reactions. A hybrid RS [8] has been suggested to provide each patient with a list of recommendations from family physicians, taking into account the temporal complexities of their relationships. A diet recommender system is suggested in [9] using a k-clique embedded deep learning classifier that recommends food products to patients according to their various health parameters, such as blood pressure, cholesterol, sugar level, weight, etc.

RS can also be designed by optimizing the objectives where each individual objective may be maximized or minimized. Optimization is a mechanism by which alternative solutions are sought and compared until there is no better solution. Optimization can be categorized as single-objective optimization and multi-objective optimization. If there is only one objective function involved in an optimization problem, the approach for finding the optimal solution is called single-objective optimization. If the optimization problem requires more than one objective function, the task of finding one or more optimal solutions is referred to as multi-objective optimization. There are many priorities involved in most real-world search and optimization issues. In a multi-objective optimization problem, there are a number of objective functions to be minimised or maximised. Mathematically, a multi-objective optimization problem can be defined as follows:

$$Minimize/Maximize f_m(x), m = 1, 2, ..., m \tag{2}$$

$$\text{Subject to } g_i(x) \geq 0, j = 1, 2, ..., j$$

$$h_k(x) = 0, k = 1, 2, ..., k$$

$$X_i^{(l)} \leq X_i \leq X_i^{(u)}, i = 1, 2, ..., n$$

Where x is a vector of n decision variables: $x = (x_1, x_2, ..., x_n)^T$. x_i is a decision variable which takes a value within a lower $x_i^{(l)}$ and an upper $x_i^{(u)}$ bound and $g_i(x)$ and $h_k(x)$ are constraint functions [10]. Different multi-objective recommender systems have already been developed to satisfy the various user and system requirements. A multi-objective concept based location recommender system [11] is proposed that takes into account the two opposing parameters, such as common preferences and individual preferences. In order to optimize these targets, this method has used a multi-objective evolutionary algorithm and evaluated Foursquare and Gowalla datasets. A novel multi-objective-based menu recommendation is proposed in paper [12] that features an optimal balance between nutritional aspects, harmony and coverage of available pantry ingredients. In paper [13], a multi-objective heuristic algorithm known as Multi-objective Hydrologic Cycle Optimization (MOHCO) is proposed to model water flow, infiltration, evaporation and precipitation processes in nature in order to find an optimal set of Pareto solutions. The suggested approach is evaluated on MovieLens 100K movie recommendation dataset and reveals that MOHCO exceeds other heuristic algorithms, including MOEAD, NSGA-II, NSGA-III and MOPSO. A multi-objective evolutionary algorithm-based RS [14] with two objectives of precision and diversity has been proposed to generate a set of non-dominated solutions where each solution denotes a specific list of recommendations for the target user. A multi-objective evolutionary algorithm [15] based on decomposition is proposed that optimises the two conflicting parameters such as the accuracy and diversity of the suggested systems and has been tested using MovieLens and Jester datasets.

In machine learning and statistics, the method of selecting a subset of specific features or variables for use in model construction is feature selection. It can be an another aspect for RSs that takes into account a collection of item features in order to produce suitable recommendations. [16] has offered a comprehensive description of the different approaches to feature selection and examined adaptive classification systems and parallel classification systems for the prediction of chronic diseases. In [17], a content-based feature selection recommendation scheme is proposed that has examined the impact of feature selection on content-based RS. [18] has implemented a system for the automated selection of content-based insightful features, which is independent of the type recommendation framework or type of features and evaluated on RSs from various domains. Predicting the risk of cancer prognosis plays an inevitable role in order to save the lives of the victims [19]. A recommendation framework is proposed in [19] to produce a reliable recommendation for the prognosis of breast cancer and the best prediction algorithm has also been proposed for breast cancer detection.

After a literature review, it is found that very few work has been done on HRS and most of them have used the traditional algorithms for recommendation purposes. It is also observed that very negligible work has done on HRS using multi objective optimization and also feature selection approaches. Therefore, this article has proposed an RS using a feature selection method based on MOGA [20] to predict the prognosis of Cervical Cancer onset in order to save the lives of women dying due to this disease.

III. Methodology

A. Analysis of Dataset

The proposed system is implemented on Cervical Cancer Risk Classification Dataset [21]. It consists of thirty-two attributes with eight hundred and fifty-eight samples. We have considered 'Biopsy' as the target class. The dataset is imbalance in nature as it contains 55 samples from class 1 and 803 from class 0 for the target attribute 'Biopsy' as shown in Fig.2. The dataset is preprocessed to handle the missing

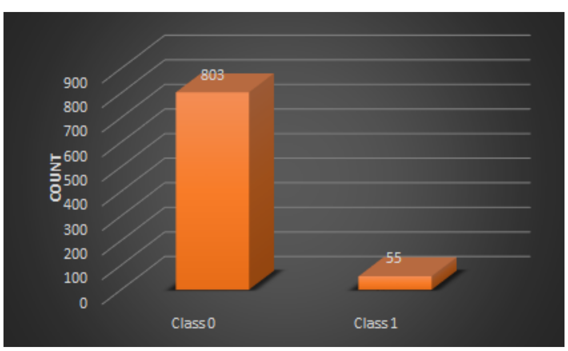

Fig. 2. Class samples of Dataset

values and imbalanceness. SMOTE oversampling method has been used in balancing the dataset.

B. Multi objective-Genetic Algorithm (MOGA)

Multi-objective optimization is an area of decision-making with several parameters in which more than one objective function can be optimised at the same time. It is used for situations with conflicting objective functions where there is no single solution that can maximise each objective at the same time. Multi objective optimization can be achieved through various evolutionary algorithms. Genetic algorithm (GA) is one of the most sophisticated algorithms for Multi objective optimization. It is a stochastic method based on the mechanics of natural genetics and biological evolution for function optimization. To generate better and better approximations, genetic algorithms work on a population of individuals. A new population is generated by selecting individuals in the problem domain according to their fitness level at each generation and using natural genetics operators to recombine them together. The flow chart demonstrating the genetic algorithm's operations is shown in Fig. 3.

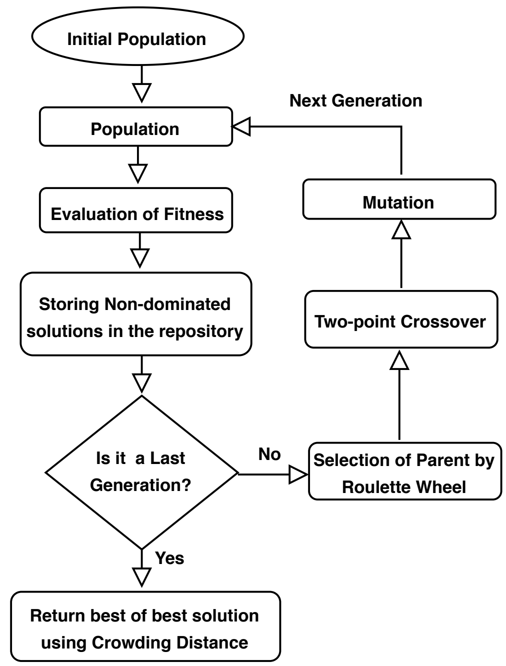

Fig. 3. Flow Chart showing Operations of Genetic Algorithm

C. Feature Selection

Feature selection [22] in machine learning refers to the process of selecting the most appropriate features in the data to speed up the training and enhance the model's accuracy. It can be used to recognise and delete unused, obsolete, and redundant features that do not add to or reduce the predictive model's accuracy. Wrapper methods, filter methods and embedded methods are the various methods for feature selection. A model is trained multiple times with wrapper methods using different feature sets and the resulting models are compared through their accuracy of cross validation. With filter methods, instead of cross validation accuracy, the features are tested against a proxy. In taking advantage of both solutions, the embedded model distorts the distinction between the two models. The proposed model has used wrapper method with K-Nearest Neighbour classifier for feature selection. MOGA has been used in this system for feature selection as GA is the most efficient evolutionary algorithm for selecting the important features with lesser complexity as compared to the other traditional feature selection approaches [23][24].

D. Framework of Proposed MOGA-RS

Risk prediction for Cervical Cancer plays an inevitable role in saving the lives of women, as it is the most preventable type of cancer. To make the women aware of the prognosis of Cervical Cancer according to their current life style activities, this proposal is aimed to develop a predictive RS using MOGA based feature selection approach. The architecture of the system proposed is illustrated in Fig 4. The proposed system

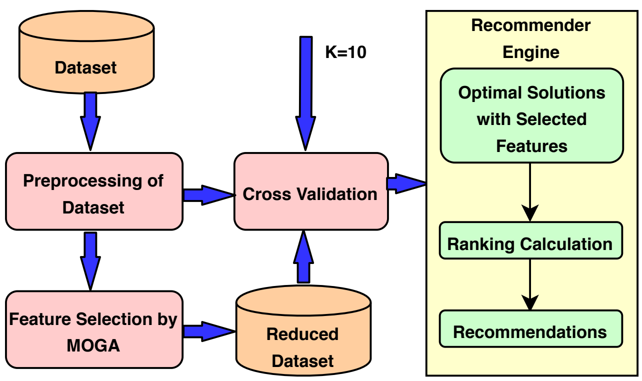

Fig. 4. System Architecture of the Proposed System

has used MOGA for feature selection with two conflicting objectives (minimization of number of parameters and maximization of accuracy) and initial population as 50. It has used various genetic operations like encoding, selection, crossover, and mutation to select the most appropriate features, and these operations are explained in the following subsections.

1) Encoding: In the encoding operation, each set of features present in the population is represented as a one-dimensional array of n-chromosomes which is referred to as one gene, where 'n' represents the total number of features present in the dataset [20]. The values of the chromosome in a gene are represented by either 0 or 1 which indicates the absence or presence of a particular feature.

2) Selection: Selection is the stage of a genetic algorithm in which individual genomes for later breeding are selected from a population. Roulette wheel selection has been used in the proposed system in which the circular wheel is divided by fitness.

3) Cross Over: The crossover is a genetic operator which is used to generate new offspring by combining the genetic information of two parents. The proposed system has used two-point crossover where two points on individual solutions are labelled at random and the strings are exchanged at these points.

4) Mutation: Mutation is a genetic operator that is used from one generation of a population of genetic algorithm chromosomes to the next to preserve genetic diversity.

5) Objective Functions: The objective function or fitness function is used as a single figure of merit to summarise how close a given design solution is to achieving the defined goals. The proposed system has used number of features (O1) and accuracy (O2) as the two objective functions as defined in equation 3 and equation 4.

$$O1(X) = \sum_{i=1}^{n} x_i \tag{3}$$

Where X is a vector of n bits.

$$O2(X) = \frac{TP + TN}{TP + FP + FN + TN} \tag{4}$$

Where
TP (True Positive): It is an outcome in which the positive class is accurately predicted by the model.
TN (True Negative): It is an outcome in which the negative class is accurately predicted by the model.
FP (False Positive): It is an outcome in which the positive class is inaccurately predicted by the model.
FN (False Negative): It is an outcome in which the negative class is inaccurately predicted by the model.

6) Multi Objective Optimization: The proposed system has used multi objective optimisation for feature selection with two conflicting objectives (minimization of number of parameters and maximization of accuracy). Initially, a set of solutions that are not dominant by other solutions is discovered and then some high-level knowledge is used to get the best solution. The Pareto Dominance principle [25] is used to achieve optimal solutions taking into account all the objectives at the same time in multi-objective optimization.

7) Updating Repository: The repository is updated after each movement of the population. The solution not dominated by the solutions which are already present in the repository is allowed to reside in the repository [18]. If any existing repository solution is dominated by that insertion, it should be excluded. The proposed system has used the concept of crowding distance [26] to handle the overflowing issue of the external repository due to restricted size of the repository defined by the user.

E. Recommendation

The set of Pareto optimal solutions got through the MOGA based feature selections are further used to provide recommendations. The system recommends the top-N features where N represents the most responsible features for the prognosis of Cervical Cancer in women and it also recommends the top-5 prediction models for the Cervical Cancer prediction. On the basis of their rank values, the features are recommended. The features are ranked according to their correlation values against the target attribute and their number of occurrences in the optimal solutions. For model prediction, the reduced datasets obtained through the optimal solutions are used. These datasets are further applied with different classifiers for accuracy prediction. It has assumed a reduced dataset and a classifier pair as a model. The models are ranked according to their accuracy values and high rank is assigned to a model with high accuracy. The top-5 ranked models are further used for model recommendation.

IV. Results and Findings

After applying the MOGA based feature selection approach to the Cervical Cancer Risk Classification dataset for 50 generations with a population size of 50, 8 sets of optimal solutions are found. The optimal solutions are of size 16 (F1), 7 (F2), 8 (F3), 13 (F4), 15 (F5), 11(F6). 12 (F7) and 9 (F8). The features present in the different optimal solutions are listed in the Table 1. The features are recommended on the basis of their rank values. The rank of the features are determined according to their ratings correspond to the correlation values against the target attribute and their number of occurrences in the optimal solutions. The features are rated in a 1-10 scale as shown in the Table 2. Rating-1 represents the rating of the feature according to its correlation values against the target attribute. Feature having high correlation value is assigned high rating value. Similarly, Rating-2 represents the rating of the feature according to its number of occurrences in the optimal solutions. Feature having high occurrence value is assigned high rating value. The features are ranked according to the average value of Rating-1 and Rating-2. Feature having high average rating value is assigned high rank and we have assigned low rank number to high ranked feature. The correlation value is used to overcome the tie if features have the same average rating value. 7 features out of 32 features present in the dataset are found out whose average rating values are greater than 5 and these features can be recommended as the most promising features for the prognosis of Cervical Cancer in women as shown in Fig 5.

TABLE I
Description of Optimal Solutions

Optimal Solution	Features Present
F1	'Age', 'Num of pregnancies', 'Smokes', 'Hormonal Contraceptives', 'Hormonal Contraceptives (years)', 'IUD', 'STDs:cervical condylomatosis', 'STDs:genital herpes', 'STDs:molluscum contagiosum', 'STDs:AIDS', 'STDs:HIV', 'STDs:Hepatitis B', 'STDs: Time since first diagnosis', 'Dx:Cancer', 'Dx:CIN', 'Dx'
F2	'Number of sexual partners', 'Smokes (packs/year)', 'Hormonal Contraceptives', 'Hormonal Contraceptives (years)', 'IUD (years)', 'STDs: Time since last diagnosis', 'Dx:CIN'
F3	'Number of sexual partners', 'IUD (years)', 'STDs:condylomatosis', 'STDs:HIV', 'STDs: Number of diagnosis', 'STDs: Time since first diagnosis', 'Dx:HPV', 'Dx'
F4	'Age', 'Num of pregnancies', 'Smokes (packs/year)', 'Hormonal Contraceptives', 'STDs (number)', 'STDs:condylomatosis', 'STDs:vulvo-perineal condylomatosis', 'STDs:pelvic inflammatory disease', 'STDs:HIV', 'STDs:HPV', 'STDs: Time since last diagnosis', 'Dx:Cancer', 'Dx:HPV'
F5	'Age', 'Num of pregnancies', 'Smokes', 'Hormonal Contraceptives', 'STDs', 'STDs:condylomatosis', 'STDs:vulvo-perineal condylomatosis', 'STDs:pelvic inflammatory disease', 'STDs:AIDS', 'STDs:Hepatitis B', 'STDs:HPV', 'STDs: Number of diagnosis', 'STDs: Time since first diagnosis', 'Dx:Cancer', 'Dx'
F6	'Age', 'Num of pregnancies', 'Smokes', 'Smokes (years)', 'STDs (number)', 'STDs:pelvic inflammatory disease', 'STDs:AIDS', 'STDs:HPV', 'STDs: Number of diagnosis', 'STDs: Time since last diagnosis', 'Dx:Cancer', 'Biopsy'
F7	'Age', 'Num of pregnancies', 'Hormonal Contraceptives (years)', 'IUD', 'STDs (number)', 'STDs:vaginal condylomatosis', 'STDs:molluscum contagiosum', 'STDs:AIDS', 'STDs: Time since first diagnosis', 'Dx:Cancer', 'Dx:CIN', 'Dx:HPV'
F8	'Age', 'Num of pregnancies', 'Smokes (packs/year)', 'STDs:vaginal condylomatosis', 'STDs:syphilis', 'STDs:pelvic inflammatory disease', 'STDs:HIV', 'STDs: Time since first diagnosis', 'Dx:HPV'

TABLE II
Ranking of Features

Feature Name	Correlation with Target	Rating-1	No. of occurrences in optimal solutions	Rating-2	Average Rating	Rank
Dx:HPV	0.242344	10	4	8	9	2
Dx:Cancer	0.242344	10	5	9	9.5	1
Dx	0.226096	9	3	7	8	3
Dx:CIN	0.150940	8	3	7	7.5	5
STDs HIV	0.138458	7	4	8	7.5	6
Num of pregnancies	0.123999	6	6	10	8	4
Age	0.118396	5	6	10	7.5	7
STDs Syphilis	-0.117722	4	1	6	5	8
STDs	0.108939	3	1	6	4.5	9
STDs (number)	0.100974	2	3	7	4.5	10

The model recommendation has been done on the basis

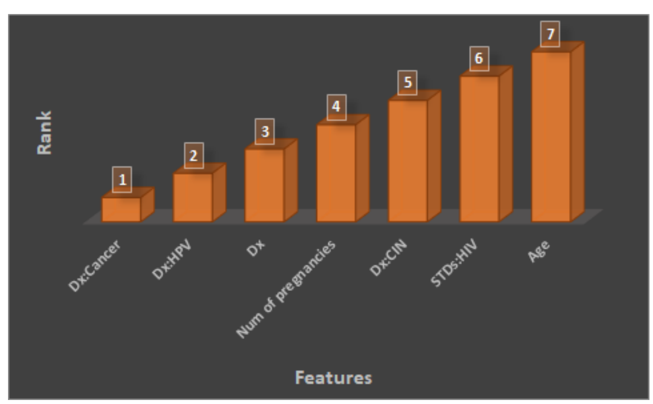

Fig. 5. The Top-7 Recommended Features

of their accuracy values. 7 different classifiers are used for the model construction namely LR (Logistic Regression), SVC

(Support Vector Classifier), DT (Decision Tree), KNN (K-Nearest Neighbour), GNB (Gaussian Naive Bayes), XGBoost (eXtreme Gradient Boosting) and GBM (Gradient Boosting Machine). We have got 56 models for 8 reduced datasets and 7 classifiers. The top 5 models with the highest accuracy values

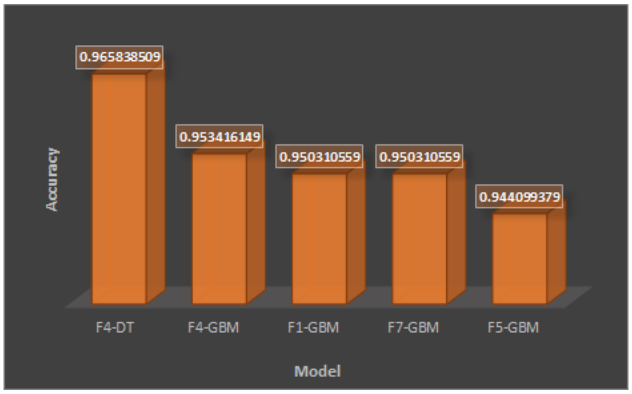

Fig. 6. The Top-5 Recommended Models

out of these 56 models are recommended as shown in Fig 6. The final Pareto front after 50th generation is shown Fig 7.

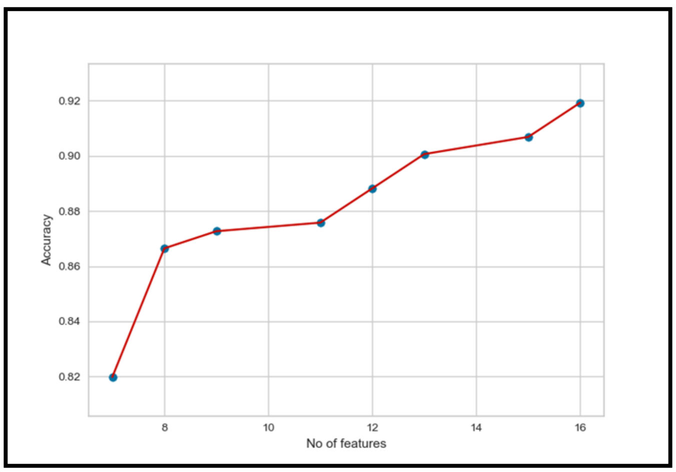

Fig. 7. The final Pareto Front

From the results of the implementation, it can be inferred that the most responsible features for Cervical Cancer prognosis according to their importance are 'Dx:Cancer', 'Dx:HPV', 'Dx', 'Number of pregnancies', 'Dx:CIN', 'STDs:HIV' and 'Age'. In order to reduce the prognosis of Cervical Cancer, women should be very much aware about these features. The descriptions of these features are shown in Table 3. It can also be concluded from the results that a model with a Decision Tree classifier demonstrates optimum accuracy and models with GBM classifiers work attractively as well.

V. Conclusion and Future Work

This article summarizes the use of feature selection approach and recommender systems for Cervical Cancer risk prediction using Cervical Cancer Risk Classification dataset.

TABLE III
Description of Top-7 Recommended Features

Feature Name	Description
Dx:Cancer	It denotes whether the victim is having other cancers or not. There is a greater risk of Cervical Cancer in people who have had breast, rectum, uterus or colon cancer.
Dx:HPV	It deontes whether the victim is infected with Human Papilloma Virus(HPV) which is primarily spread through sexual interaction. There are more than 100 HPV types, at least 14 of which are cancer-causing. 70 percent of cervical cancers and pre-cancerous cervical lesions are caused by two HPV types (16 and 18).
Dx	This represents whether the victim is examined to ascertain the extent of the condition.
Number of pregnancies	It is the total number of confirmed births that a woman has undergone. It is associated with a reduced risk of Cervical Cancer because women ovulate less frequently when pregnant .
Dx:CIN	It indicates whether the victim has Cervical Intraepithelial Neoplasia (CIN), which is the irregular development of cells that may possibly lead to cervical cancer on the surface of the cervix.
STDs:HIV	It denotes whether the victim is living with a person having HIV who become infected with HPV. Such women are having high risk of the prognosis of Cervical Cancer
Age	Regardless of age, all women are at risk of developing Cervical Cancer. However, women aged 55-64 years have the highest risk of Cervical Cancer.

It recommends the most promosing features responsible for the Cervical Cancer prognosis in women so that the women can make themselves aware to this disease in their lives. It has also recommended some prediction models with high accuracy for prediction of Cervical Cancer. This research work may be further enhanced in order to include recommendations for hospital and medical insurance policies to support women at high risk of this disease.

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