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Machine Learning-Based Hybrid Recommendation (SVOF-KNN) Model For Breast Cancer Coimbra Dataset Diagnosis

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Abstract— An effective way to identify breast cancer is by creating a prediction algorithm using risk factors. Models for ML have been used to improve the effectiveness of early detection. This article analyses a KNN combined with singular value decomposition and Grey wolf optimization(GWO) method to give a detection of breast cancer(BC) at the early phase depending on risk metrics. The SVD technique was utilized to eliminate the reliable feature vectors, the GW optimizer was used to select the feature vectors, and while KNN model was used to diagnose the BC status. The proposed hybrid recommendation model (SVOF-KNN) for BC prediction's main objective is to give an accurate recommendation for BC prognosis through four different steps such as;BCCD dataset collection, data pre-processing, feature selection, and classification/recommendation. It is implemented to classify the consequence of risk metrics connected withregular blood analysis(BA) in the BCCD database. The aspects of the BC dataset are insulin, glucose, HOMA, Leptin, resistin, etc. The error categories such as RMSE and MAE are used to calculate the exception values for each instance of the BC dataset. It hybrid model has recommended the best score instance having the minimumexception rateas the defined features for BC prediction. It improves significance in automatic BC classification with the optimum solution. The hybrid recommendation model (SVOF-KNN) also recommends the accurateclassification method for BC diagnosis. The results of this work shall enhance the QoS in BC care.

Keywords- HRS (healthcare recommendation system); ML (Machine learning); SVOF-KNN model; SVD (singular value decomposition) feature extraction; GWO (grey wolf optimization)feature selection; BCCD (breast cancer coimbra dataset); MAE (means absolute error), RMSE (root means square error).

I. INTRODUCTION

The learning models were used to assess the health data to identify health risks, as large-scale, high-dimensional (HD) datasets have currently been available across a variety of fields and technologies [1]. One of the key causes of breast cancer (BC) death as well as one of the major worldwide health issues [2]. The most common cancer is breast cancer which is presented in females, and one of the killers of females [3]. According to the WHO, three out of every 10 females who received a BC diagnosis worldwide passed away in 2020 [4]. Due to its stealthy progression, the majority of BC diseases are found during routine screening [5]. BC incidence, mortality, and survival rates may be impacted by several variables, including the environment, genetics, way of life, and population structure [6]. When BC is found early and treated, the chance of survival is very good [7].

BC is affected by two main factors modifiable and non-modifiable. The modifiable factors (MF) are individuals that can be managed, such as environmental problems and behaviors, and other type factors are those that can't be addressed, such as gender and personal history [8]. According to a review, one out of twenty-eight females across India is

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disposed to breast cancer as the current detection methods are inadequate to forecast the existence of BC in the precise estimate of the disease. Furthermore, limited awareness, proactive actions, and treatment services raise survival risks. Detecting the syndromes at an initial state provides direction to resolve BC using a suitable treatment [9].This type of cancer is regarded as a multifactorial syndrome; around 30% of women are affected with breast cancer [10, 11]. Approximately 1.5 million females have identified with BC annually, and 5 lakh females die worldwide. In the previous thirty years, this type of disease raised whereas death-ate has reduced. Still, mammography screening reduces the death rate and is evaluated by 20%, and enhancement in cancer diagnosis is evaluated at sixty percent [12] [13]. The mammography treatment can evaluate irregular breast cancer tissue in the family with delegated and common malignancy symptoms. Because of many images, this approach is unsuitable for assessing assumed cancer zones. According to a survey, around fifty percent of BCs remained not identified in the screening of females with identical compact breast tissue [14]. Still, approximately a quarter of females through BC are analyzed harmfully in 2 yrs. of broadcast. So, the initial and appropriate treatment of cancer (breast) is essential [15] [16]. The large quantity of fatty and fibrous tissues of BC initializes irregular evolution which becomes the reason for BC.

The tissues of cancer cause various phases of cancer, and several forms of breast cancer arise in affected tissues, and cells spread through the human body [17]. Fig 1 represents different types of breast cancer.

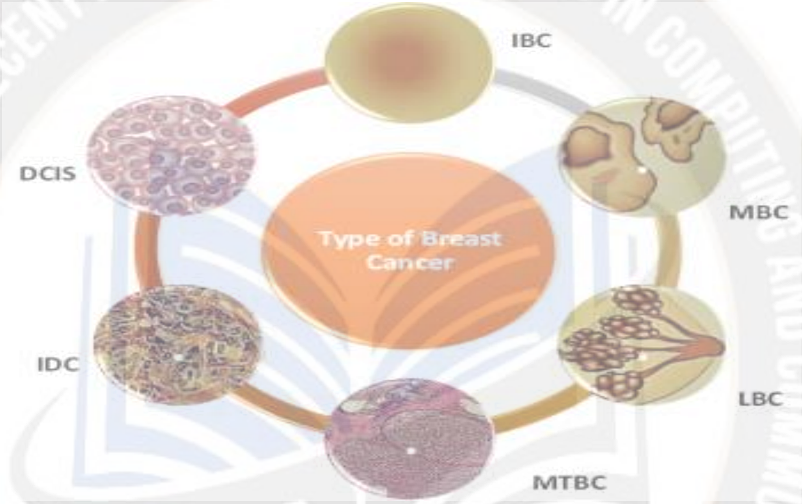

Figure 1. Categories of Breast Cancer [18]

a) *Ductal carcinoma in Situ (DCIS)[19]:* This category of BChappens while spreading irregular cells outside the breast. This type of cancer is also called non-invasive and is the most common cancer, accounting for most situ cases. It is not severe due to the abnormal issues are not developed out of the breast. Still, it can potentially grow into IDC (invasive ductal carcinoma). Between biopsy-proven DCIS patients, around 20-25% are surpassed to IC (invasive carcinoma) once they suffer definitive surgery like lumpectomy and mastectomy [20] [21].
b) *Invasive Ductal Carcinoma (IDc):* It is also a category of BC called infiltrative ductal carcinoma [15]. The IDc occurs during the spreading of irregular tissues whole of the breast cells, and that type of cancer mainly exists in men [22][23].
c) *Mixed tumors breast cancer (MTBC):* This category of BC is also called invasive mammary [24]. The irregular and lobular issues are reasons for MTBC breast cancer [25]. The MTBC is considered regular global care [26].
d) *Lobular breast cancer (LBC) [27]:* It is another type of breast cancer that arises inside the lobule and increases the probability of another invasive cancer. Early, an excess of LBC with varied ductal and lobular histology (LH) is determined concerning HDGC.5 – eight such DGC. LBC represents histological types regularly with a lack of cell-cell adhesion.
e) *Mucinous breast cancer (MBC) [28]:* This type of cancer occurs due to invasive ductal tissues, and this type of breast cancer is called colloid BC. It rises during the spreading of abnormal cells around the duct [29].
f) *Inflammatory breast cancer (IBC) [30]:* This category of BC that reasons swelling and blushing of the breast, which is a rapidincreasing type of BC. After the lymph vessels block in breakdown tissues, the IBC category of cancer becomes visible.

There are several kinds of issues in postmenopausal females. The level of vitamin D is low, and current research recommends that females lacking vitamin D levels increase the risk of BC. Vitamin D is essential for controlling the

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average breast tissue growth and can block the growth of breast cancer cells. Another issue is light contact at night. Different surveys are recommended for females who work at night, such as workers, hospital staff, military, etc. these people have more risk of breast cancer. Another issue is contact with chemicals in cosmetics, and some of the compounds in cosmetics pay to cancer growth in people. Chemicals in food are also a risk factor in increasing the chances of breast cancer [31].It provides an alternative method to standard prediction modeling used to find existing problems and enhance the accuracy of the breast cancer system [32].

ML methods were established from recent surveys of recognition and computational learning. It can develop fewer assumptions based on computational methods and recognize the problematic interactions between varied risk factors. It is obtained using reducing particular objective functions of analysis and predicted results [33. ML is required for prediction system development that is analyzed the forecast and survival of cancer and produces better accuracy and reliability estimations [34] [35]. ML is an automatic technique for understanding, and algorithms are developed to study previous or existing datasets [36].

Supervised and unsupervised learning are both primary ML methods [37]. The superset consists of a labeled set of training data and unsupervised is based on an un-labeled collection of training data. It primarily represents a computer-vison-based decision-making model that provides recommendations as per need [38]. This type of model synonymously provides better filtering known as anmachine. The recommender models are dynamic online data filtering models that include different paradigms in figure2.

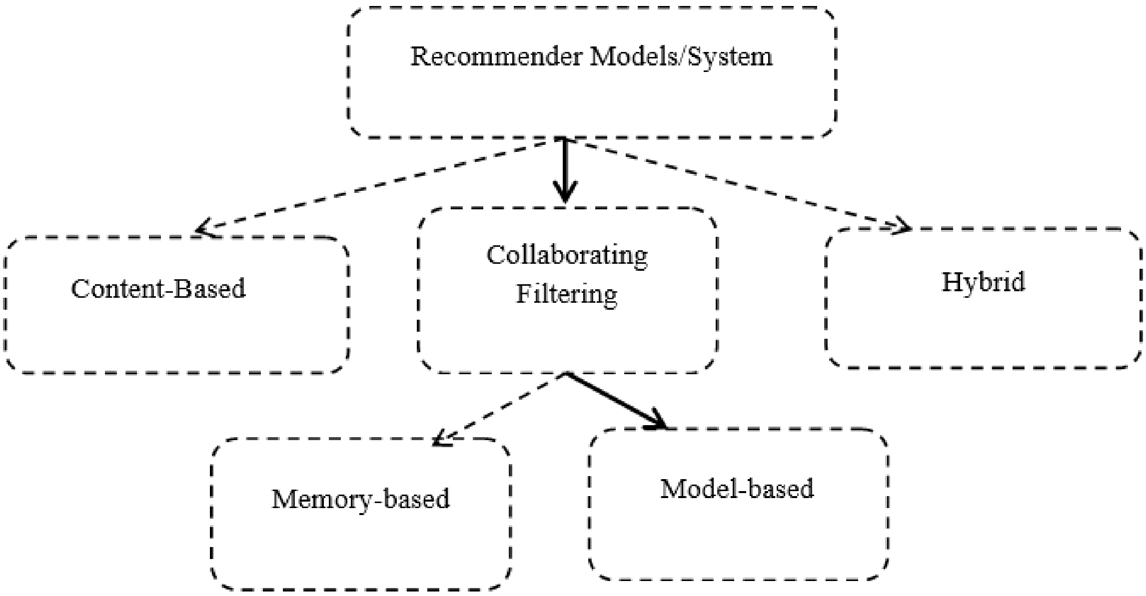

Figure 2 .Different Categories of Recommender Systems [42][39].

Ganjar Alfian et al. (2022) [41]analyzed anSVM merged with an extra tree (extremely randomized trees) classifier to offer detection of BC at the earlyphase depending on risk metrics. An extra-tree classifier was utilized to eliminate the inappropriate featuresets, while an SVM classifier was used to predict the BC position. BC dataset comprising 116 subjects was used by ML models to detect BC, while the 10-fold cross-validation was engaged for the prototypical calculation. The combination of SVM and Extra-trees model achieved the maximum accuracy rate that was importantly better than the other classifiers. Kanimozhi et al.[42] presented anML-based recommender system to predict breast cancer. Information gathering, preprocessing, learning, evaluation, verification, and forecasting were the four steps of the suggested "Machine learning-based recommendation systems[40] for breast cancer detection," which intends to offer an accurate recommendation for breast cancer prediction. The existing methods provided effective results, but in some cases, the reliability of the current methods is poor. There is a need for advanced techniques to improve reliability and provide more efficient outcomes.

This research article is arranged as trials: Sec 2 describes prior work on classification or recommendation and feature extraction methods like SVD, PCA, SVM, ANN, NB, and KNN. Sec 3, Material describes the dataset for

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implementation of the proposed work. Sec 4 describes the proposed system and its different steps such as data collection, preprocessing, feature selection, classification, and recommendation system. The experimental results of the proposed work, arithmetical metrics such as accuracy, SP, SN, MAE, RMSE, and Error rate. After this section, explain the comparative analysis using different classification and recommendation models defined in sect 5. Sec. 6 shows the conclusion and further extends the research work.

II. RELATED WORK

This section represents the study of additional research based on the detection of BC. It is the most dangerous disease in the world. Several kinds of research have been done on breast cancer disease. Various frameworks, methods, and models are developed using patients' clinical data to predict breast cancer in the early stage. Table 1 defines the different methods, datasets, performance metrics, existing research gaps, and problems in analyzing breast cancer classification and recommendation in data mining. It represents the work that has been introduced by several analyzers using breast cancer disease datasets. Generally used classification or recommendation and feature extraction methods like SVD, PCA, SVM, ANN, NB, KNN, etc are briefly explained and proposed ML classifiers to develop a classification and recommendation system.

Table 1. Work Completed To Classify The Disease By Several Investigators.

Publication Year	Database	Proposed Methods	Performance Metrics	Language
Ahmed et al. (2018) [43]	i2B2 datasets	Novel semi-supervised technique to recommend disease labels using clustering and frequent pattern mining.	Pre Rec	JAVA
Kanimozhi et al. (2020) [42]	BCCD dataset	MLRS-BC motives to give anprecision recommendation for BC detection through different steps.	RMSE MAE	PYTHON
Muhammet Faith et al. (2018) [44]	UCI Library	ELM SVM KNN ANN	Acc. Train time RMSE	MATLAB with GUI interface
Kemal et al. (2018) [45]	BCCD dataset	KMC MAD method AdaBoostM1	Acc. Pre Rec TP FP ROC curve KV F-measure	No
Yolanda et al. (2021) [46]	CBCD dataset	KNN Logistic (L1, and L2) Linear SVM (L1, and L2) Non-linear SVM DT RF GB NB	Acc. Training time Testing time	Screening Tool (WEKA)
Miguel et al. (2018) [47]	WBCD dataset	SVM	SN SP AUC	ML tool
Srwa et al. (2021) [48]	WBCD dataset	SVM KMC KNN DT Regression methods	Acc.	WEKA
Karthik et al. (2019) [49]	WBC dataset	DNN RFE	Acc. SP SN Pre Rec	No

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Abbreviations: BCCD (breast cancer Coimbra dataset); MLRS-BC (machine learning-based recommender system for breast cancer prediction); RMSE (root means square error rate); MAE (mean absolute error); Pre (precision); Rec (Recall); ELM (extreme learning machine), SVM (support vector machine); ANN (artificial neural network); KNN (K-nearest neighbor); MATLAB (matrix laboratory); KMC (k-means clustering); Acc. (accuracy); TP (true positive); FP (false positive); ROC (receive operation curve); KV (kappa value); MAD (mean absolute deviation); CBCD (coimbra breast cancer dataset); DT (decision tree); RF (random forest); GB(gradient boosting), NB (naïve bayes); WBCD (Wisconsin breast cancer dataset); SP (Specificity); SN(sensitivity); ML (machine learning); DNN (deep neural network); RFE (recursive feature elimination).

III. MATERIALS

The dataset name is “BCCD database”taken from the UCI ML dataset [50] to model the SVOF-KNN recommender model, which has been implemented. BCCD database, there are 2 classes and 9 features. The category division of the database is fifty-two data points relating to the healthy class, and sixty-four data relating to the patient class. Fig 3 defines the box plot depictions of the BCCD dataset and the class divisions of the BC dataset are defined in fig 4. When seeing at this fig 4, the perception of this database is too complex as the fit and patient class.

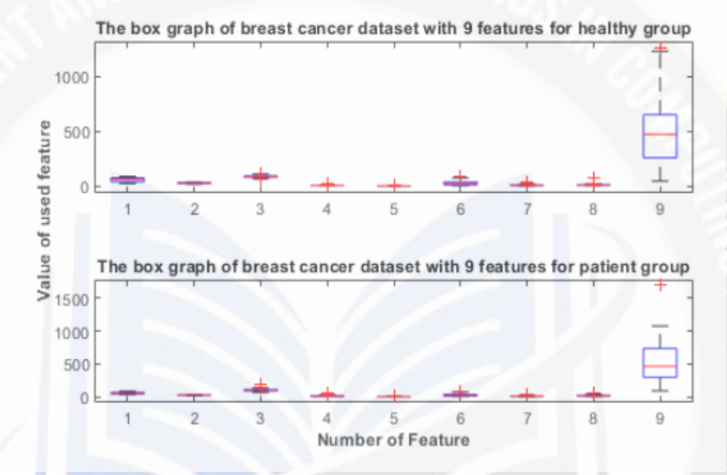

Figure 3. BCCD dataset (Box Representation) [45]

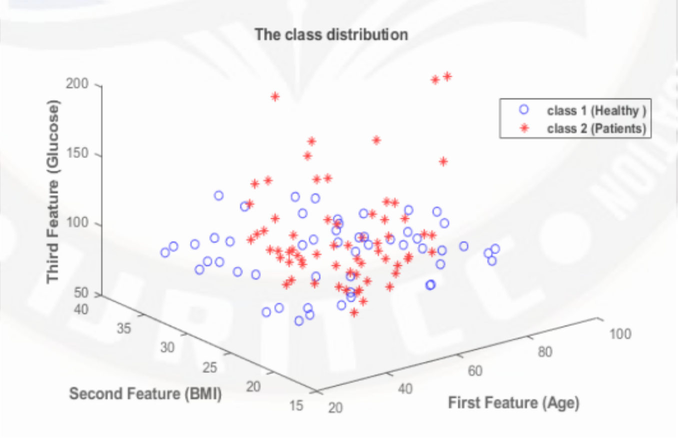

Fig 4. BCCD Dataset (Class Division) [45]

The BCCD database has a composing class division, but the class division of the BC database has a linearly non-separate database. So, a recommendation technique might be utilized to improve the metrics.

IV. PROPOSED SYSTEM

The researchmodel is implemented in the hybrid recommender model (SVOF-KNN) for the recommendation process, Singular value decomposition (SVD) is used for feature extraction, and the GWO is used for the feature-selecting method. These methods are for choosing a sub-set of features from all defined featuresets. The phases included in the research model are defined below, and it is presented in fig 5.

- Data collection (UCI-ML repository site).

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- Data preprocessing (Remove missing values and clear data values).
- Feature selection using SVD (choosing the best feature and eliminating the irrelevant features).
- Hybrid Recommended model ((SVOF-KNN).
- Performance Metrics: Accuracy, SP, SN, Error Rate, MAE, and RMSE.

A. Data Collection

The statistical and definite attributes of the BCCD database used for this proposed analysis were attained from UCI online ML repo. The dataset explored can be seen simply through any software such as Notepad, or MS-excel. This category of the dataset is generally statistical whereas cancer type is denoted by a category 1 and 0.

- *Dataset Description***:** There are ten analysts, a binary dependent variable, and all quantitative, demonstrating the absence/presence of BC. The analysts are ANTHROPOMETRIC information and metrics that can be composed in the predictableBA. Analyst methods depend on these techniques, if precise, may be utilized as BIOMARKER of BC.
- *Attribute Data***:** Table 2 represents the information on attributes such as quantitative attributes and labels. Fig 6 represents the BCCD breast cancer dataset.

Table 2 Quantitative Attributes [29]

Attribute Names	Units
Age	Yrs
BMI	Kg/m2
Glucose	Mg/dL
Insulin	µU/mL
HOMA	-
Leptin	ng/mL
Adiponectin	µg/mL
Resistin	ng/mL
MCP-1	pg/dL

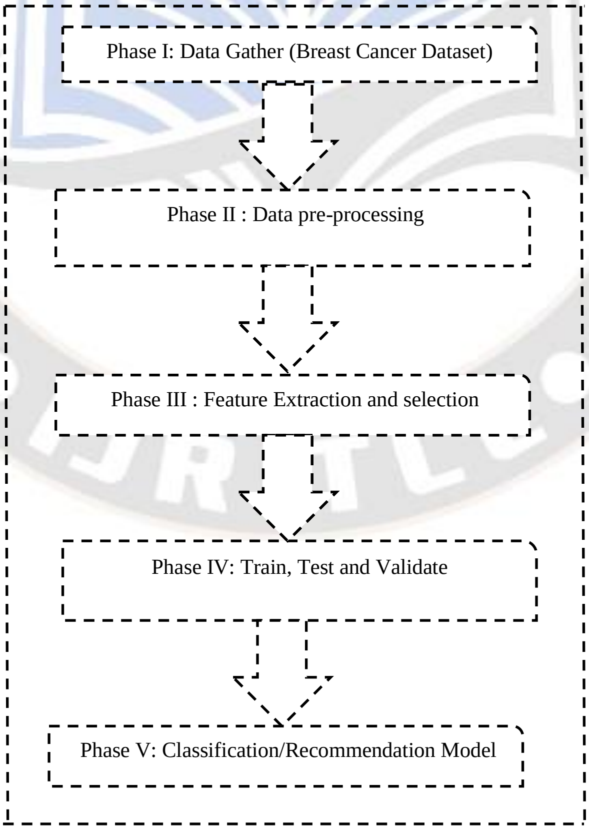

Figure 5. General Diagram of Hybrid recommender Model

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	1	2	3	4	5	6
1	Age	BMI	Glucose	Insulin	HOMA	Leptin
2	48	23.5000	70	2.7070	0.4674	8.80
3	83	20.6905	92	3.1150	0.7069	8.84
4	82	23.1247	91	4.4980	1.0097	17.93
5	68	21.3675	77	3.2260	0.6127	9.88
6	86	21.1111	92	3.5490	0.8054	6.69
7	49	22.8545	92	3.2260	0.7321	6.83
8	89	22.7000	77	4.6900	0.8908	6.96
9	76	23.8000	118	6.4700	1.8832	4.31
10	73	22	97	3.3500	0.8015	4.47
11	75	23	83	4.9520	1.0138	17.12
12	34	21.4700	78	3.4690	0.6674	14.57
13	29	23.0100	82	5.6630	1.1454	35.59

Figure 6. Dataset Representation

B. Data Pre-processing

Since the BCCD dataset is now available in raw text format, the data preprocessing phase plays a main role in the complete process. This step is required for good data representation. Data pre-processing also comprises the missing value in the dataset that might be replaced in different ways. One of the techniques is to swap them by 0 values, but this can mitigate the productivity of the research model. So, the most capable way is to swap the missing values in the database by the MEAN value of the dataset column.

C. Feature Extraction and Selection

Before feature selection, applied feature extraction step which is the main parameter for evaluation systems applied to diagnosis. Enhancing the feature selection performance might enhance the classification or recommendation performance. The most famous method for dimensionality reduction in ML is the SVD with the GWO optimization method. The SVD method is used for dimensionality reduction when applying predictive methods. The dimensional reduction includes optimizing the no. of input variables in modeling information. This method from linear algebra (LA) that utilized to automatically perform dimensionality reduction.

The correlation matrix method is merged with the heatmap feature selection (FS) approach for this dataset. The degree of correlation among the dependent and independent features may be used to assess CM. The heatmap shows the features, defined in below table 4. Using this matrix the relevant featuresets such as age, BMI, etc. were selected to attain maximum detection performance. Fig 7 defines the attributes ranking for the BC dataset created by the hybrid recommender (SVOF-KNN) model. The research work analyzed the significance of the feature sets so that the important attributes may be utilized for the recommendation method input.

Table 3. HeatMap Matrix

Age	-0.061	0.026	0.069	-0.017	-0.0033	0.043	0.026	-0.052	0.062
BMI	-0.069	0.061	0.157	-0.090	-0.018	-0.038	-0.085	0.069	-0.045
Glucose	-0.081	0.046	0.113	-0.108	-0.027	0.013	0.132	0.143	0.008
Insulin	-0.13	-0.07	0.104	-0.099	-0.0016	-0.015	-0.0096	0.061	-0.036
Homa	-0.112	-0.008	0.16	-0.11	0.010	-0.054	-0.0	0.08	-0.06
Leptin	-0.077	0.02	0.08	0.05	-0.002	0.07	0.02	0.018	-0.0004
Adi	-0.181	-0.13	0.16	-0.19	-0.016	-0.081	-0.012	0.08	-0.05
Res	-0.0431	0.131	0.1640	0.046	-0.013	0.007	-0.032	0.050	-0.020
MCP	-0.022	0.138	0.151	-0.006	0.022	0.0025	-0.025	0.0215	0.006
	Age	**BMI**	**Glucose**	**Insulin**	**Homa**	**Leptin**	**Adi**	**Res**	**MCP**

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The FS (feature selection) should be approved without failing the evaluation of the ML methods. Hence, the high-quality features are attained through the correlation coefficient attained using the heatmap defined in table 3. The heatmap is the demonstration of the correlation coefficient among distinct features. Provisional the threshold (th), the instances or attributes taking minimum correlation are measured as different feature sets.

1) SVD (Singular Valued Decomposition)

Figure 7 shows the SVD feature selection method. This method is a general arithmetic decomposition[51] defining latent semantic indexing (LSI) that is normally utilized in finding and saving data under texture document form. The objective of this method is as trails:
For a defined matrix B (a*b), matrix B is disintegrated of the multiply of three matrices as the subsequent form:
$B = V\,\Sigma\,X^t$, ………….. (i)
Hereeq(i), V is the a*a orthogonal matrix (OM) having the left singular vectors (SVs) of B as its columns. X is the b*b orthogonal matrix having the right SVs of B as its columns.
$\Sigma$is the a*b diagonal matrix having SVs, not adverse and the order is descendent:
$\delta 1 \geq \delta 2 \geq \delta \min(a,b) \geq 0$.
The matrix rank B is equal to the no. of non-zero SVs. Generally, B is the spare matrix (SM) with the maximum size.
To optimize the dimensional no. of the matrix, generally, matrix B is estimated as a matrix B_k with a minimum rank than R. The estimate matrix of B with this method is $B_k = V_k \Sigma X_k^t$, of that:
Here, V_k is the OM a*k with columns k, initial columns of matrix V.
$\Sigma_k$is the diagonal matrix k*k comprising initial characters δ_1, δ_2 …….. δ_k on the major diagonal.
X_k is the OM b*k with column k, initial columns of matrix X.
X_k is the OM b*k with column k, initial columns of matrix X.

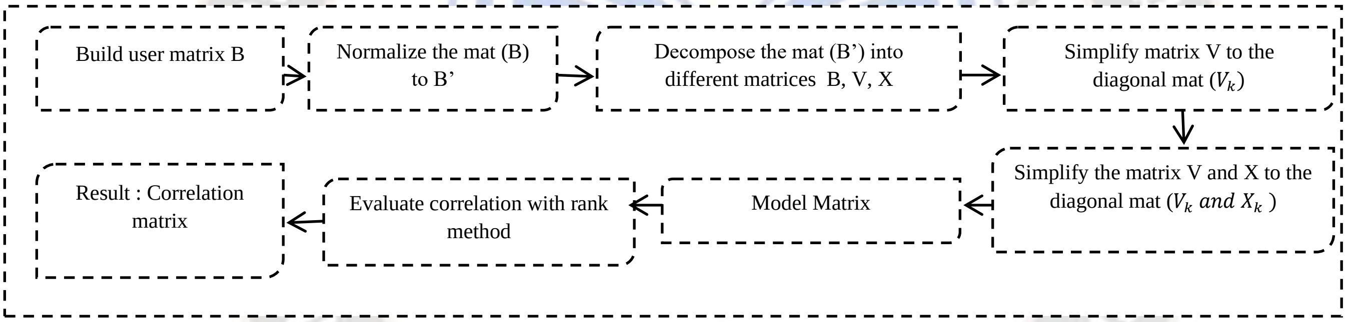

Figure 7. Flowchart Of Feature Selection Method

This estimation is measured as interchanging the recent space (r dim) into k dim. space, where k is the minimum of R.
Initially, an individual text document is modeled into a column vector in the space verified by B_{a*b} . After eliminating B_{a*b} to B_k, all the recent vectors are defined on the space B_k to get the dimensional no. of k as the formula in eq (ii):
Proj (a) = $A^t U_k \Sigma_k^{-1}$ ….. …….. (ii)

D. Proposed Steps of Hybrid (SVOF-KNN) Recommender Model

The proposed steps of the hybrid (SVOF-KNN) recommender model are elaborated in fig 9. The proposed flow of each step of the hybrid (SVOF-KNN) recommender model is described herein:

1) *Collection of breast cancer data:* This step collects required data about the patients and makes a patient simulation profile with related attributes. This step depends on BCCD [50] from the online ML-based repo.thesite, which has ANTHROPOMETRIC information health metrics of the patients.
2) *Data pre-processing***:** It applies the database as initial and removes the reliable feature sets. So, the outcome is approved for learning the information to attain the patients' feature sets. FS is the procedure of choosing reliable feature sets.
3) *Training and Testin*g: The particular feature sets are separated into train and test sets in this step. The train set is utilized for knowledge, and the test set is utilized for prognosis.
4) *Recommendation Model:* A prediction method has been implemented for the training and testing information to calculate the plan presentation metric, depending on the FS (feature selection). The hybrid (SVOF-KNN) recommender model is the best reliable featurebased on

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the presentation parameters. This proposed method also predictions the idea machine learning-based model for classification.The attribute ranting for the BCC was created by the hybrid (SVOF-KNN) recommender model. The hybrid (SVOF-KNN) recommender model assigns a rating using six scales for the attributes. The simulation attributes rating on the method is attained. When the error percentage is below 10 ratings assigned 6 means the best rating or highly recommender method is used in the proposed model. Then, an error percentage above 80 percent means the worst rating or methods selected by this model.

The hybrid (SVOF-KNN) recommendation model is simulated using ML (machine learning) library in MATLAB 2018a to propose a recommender method with reliable, precise values. The proposed hybrid “singular value optimized Feature-based KNN” recommender model is from the ML-based model. In this proposed model, the no. of neighbors combined to calculate an approximation is required minimum than the centroid “K”. In This proposed work, the singular value optimized Feature-based KNN recommender method is used for recommendation analysis. The proposed method has been implemented for recommendation: the extract of the features and selection of reliable attributes from between the healthcare database attributes and optimized ML-based method to be selected for prediction and recommendations.

- *Grey Wolf Optimization) GWO Method*: This method relates to the category of swarm-intelligence (SI) based techniques, whose employment is encouraged by the actions occurring in the natural world. It was introduced by Mirjalili et al. (2014)[52] to simulate the hunting scenario of GWs. The wolf's pack is normally categorized into 4 classes such as; Alpha, Beta, Delta, and Omega depending on the wolf’s role to assist in the hunting procedureshown in fig 8[52].

Statistical models the hunting nature of the GWs, measuring the position of the Alpha wolf (α) as the OS (optimal solution). The 2nd OS is defined by the position of the Beta wolf (β) and 3rd OS is defined by the delta wolf (δ). All the remaining outcomes are measured to be omega (ω). The hunt for the OS is defined by $\alpha, \beta, \delta, \omega$.

Eq (iii) and (iv) define the statistical model of the encircling nature of the GWs.

$$d = \left|c.x_p(T) - x(T)\right|, \dots\dots\dots\dots\dots\dots\dots\dots (iii)$$

$$x(T+1) = x_p(T) - a.d, \dots\dots\dots\dots\dots\dots\dots (iv)$$

Here, T represents the current epochs, a and c are co-efficient vectors, x_p is the location vector of the prey, and x defines the location vector of GW. These vectors a and c are evaluated as subsequent:

$$a = 2a.r_1 - a, \dots\dots\dots\dots\dots\dots\dots (v)$$

$$c = 2.r_2 \dots\dots\dots\dots\dots\dots\dots (iv)$$

Here, r_1 and r_2 are random vectors in range (0,1), and components of vector a are linearly minimized from 2 to 0 throughout epochs.

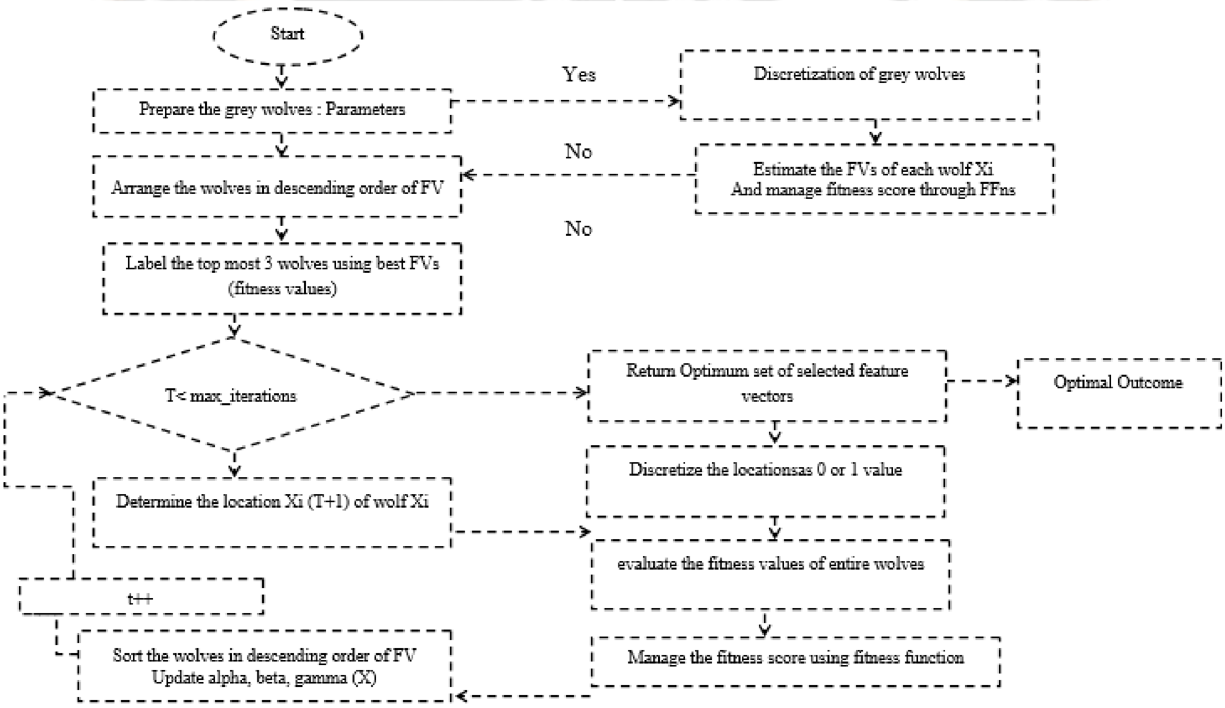

Figure 8. Flowchart GWO Optimizer

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- Hybrid Recommender Model (SVOF-KNN):With the increased mainly focus on the early-stage classification of BC, the leading necessity of any BC detection system is to precisely classify/ recommender the behavior of cancer/tumor.

Feature selection is a well-defined way of improving the recommendation KNN of any recognition system shown in fig 9.

In the proposed work, we have used the strengths of the improved GWO method to verify the optimal subset of feature sets to efficiently verify the BC tumor. The sub-set of features chosen by improved GWO is then used to train the KNN classifier. Fig 8definesthe sample position vector (PV) of an alpha search agent (SA) of improved GWO used for FS. The PV of any SA of improved GWO for FS comprises series 0 and 1. For an m-dimensional issue, the PV would comprise m–bits. The Lth feature is chosen if the value of Lth(bits) =1; otherwise, this feature will not be chosen (L= 1,2,….m). So, every SA defines a sub-set of features. The no. of feature sets chosen is equal to the no. of 1's in the PV.

The attribute ranting for the BCC was created by the hybrid (SVOF-KNN) recommender model. The hybrid (SVOF-KNN) recommender model assigns a rating using six scales for the attributes. The simulation attributes rating on the method is attained. When the error percentage is below 10 ratings assigned 6 means the best rating or highly recommender method is used in the proposed model. Then, an error percentage above 80 percent means the worst rating or methods selected by this model.

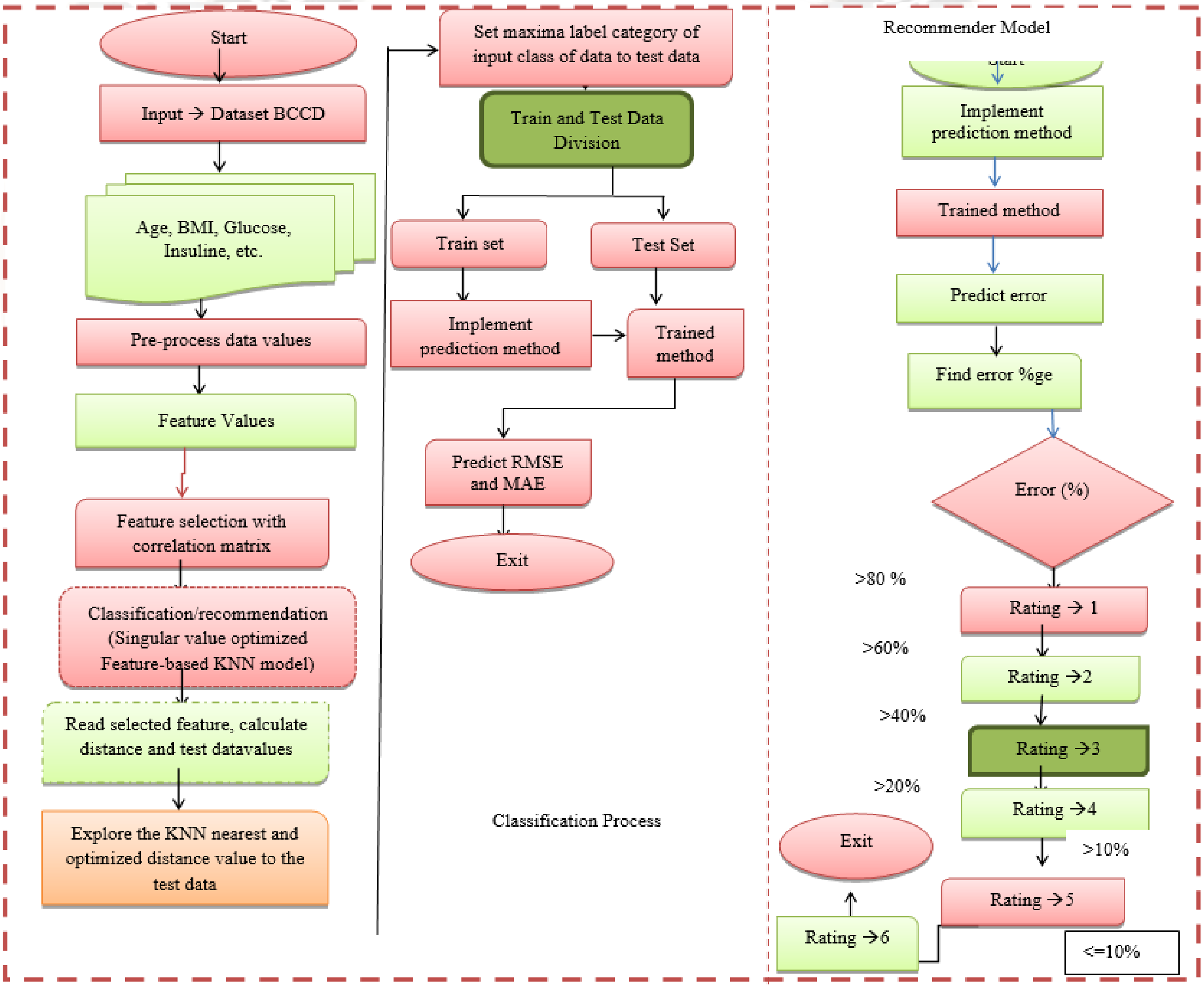

Fig 9 Hybrid Recommender (SVOF-KNN) Model

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The fitness of SA is determined by the classification and recommendation accuracy rate of the KNN classifier trained using the sub-set feature sets defined by it. The following eq. defines the FFn (F) utilized in the proposed work to calculate the chosen feature sets:

F = accuracy, ……. (vii)

Where eq (vii) accuracy is the recommended accuracy rate of the KNN classifier.

Pseudo Code: Hybrid Recommender Model (SVOF-KNN)

Input Data:

- **Train_data (d)**
- **No. of features (dimensions)**
- **The population of GW (n)**
- **No. of epochs (T)**

Outcome: Relevant feature sets chosen for classification and recommendation.

Step 1: Start

- Randomly initialize the GW population {X_j (j=1,2,3,……. , n)}
- Discrete the locations of SA from 0 to 1 as trails:

For each SA {X_j (j=1,2,3,……. , n)}
For each feature **{X_j^m (m=1,2,3,……. , dimensions)}**
If (random () >0.5)
X_j^m = 1;
Else
X_j^m = 0;
End if
End for
End for

- Evaluate the fitness of each SA (Fj) using the classification accuracy rate of the KNN model**.**
- Manage the fitness of each SA through FFn shown as trails:
- Set SA in the decreasing order of their FV.
- Suppose: Xα : Best SA (alpha wolf); Xβ: 2nd best SA (beta wolf); and X**δ** :: 3rd best SA (delta wolf).

Step 2: Optimzation (feature selection)
Set the current_epochs (T) = 0;
While (t<T)
For each SA {X_j (j=1,2,3,……. , n)}
For each feature **{X_j^m (m=1,2,3,……. , dimensions)}**
Update the position of current SA;
End for
End for
Again discrete the position of SA from 0 to 1 ass trails:
For each SA {X_j (j=1,2,3,……. , n)}
For each feature **{X_j^m (m=1,2,3,……. , dimensions)}**
If (random () >0.5)
X_j^m = 1;
Else
X_j^m = 0;
End if
End for
End for

- Evaluate the fitness of each SA (Fj) using the classification accuracy rate of the KNN model**.**
- Manage the fitness of each SA through FFn shown as trails:

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- Set SA in the decreasing order of their FV.
- Suppose: Xα : Best SA (alpha wolf); Xβ: 2nd best SA (beta wolf); and X**δ** :: 3rd best SA (delta wolf).

  t++;

end while
return Xα
After classification KNN model :

- Evaluate parameters (RSME and MAE)
- Evaluate the error percentage

If error > 80%
Rating =1;
Else if error >60%
Rating =2;
Else if error >40%
Rating =3;
Else if error >20%
Rating =4;
Else if error >10%
Rating =5;
Else (<=10%)
Rating =6;
End if
After that rating decide the higher recommender model (MLRS-BC with KNN) model, SVM and Extra Trees, and Hybrid recommender (SVOF-KNN) model) preferred.
Evaluate the performance metrics such as accuracy, SP, SN, MAE, RSME, and Error Rate.
Comparison Analysis.
Exit

V. EXPERIMENT RESULT ANALYSIS

In this research, hybrid recommender model (SVOF-KNN), simulations were carried out using a singular value optimized Feature-based KNN recommender model. This prediction approach projects the risk of BC using a singular value-optimized Feature-based KNN recommender model. It classifies the best classification concerning the parameters such as SP (Specificity), SN (Sensitivity), RMSE, ER, and MAE.

a) *Mathematical Metrics***:** In the initial phase, the satisfied of the BCCD dataset is uploaded, and the BC information is preprocessed for FE (feature extraction) and selection and classes. Now, the dataset is uploaded in the reading class for the exception recommendation model. So, the train and test division is evaluated on the BC database for the recommendation and classification model depending on the error percentage in the form of RMSE and MAE values. After finding an error percentage > 80 to 10 and then rating values are divided into 1 to 6 cases. The Error values are evaluated by [22] by using eq (viii), and (ix).

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{j=1}^{N}\left(Y_j - Y'_j\right)^2} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(viii)}$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{j=1}^{N}\left|Y_j - Y'_j\right|^2 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(ix)}$$

Here, Yj defines the targeted value, and Y'_j defines the classified value.

The proposed model defines the classification and recommendation model parameters depending on the value of all cross-validations. The proposed model performance metrics are SN, SP, and Accuracy rate. The formulas are:

- **SP (specificity)** defines the possibility of a test positive, conditioned on truly being positive. Arithmetically, this can also be defined in eq (x) :
- $\mathrm{SP} = \frac{\text{no.of TNs}}{\text{no.of TNs+no.of FPs}}$ ……………… (x)
- **SN (sensitivity)** defines the possibility of a test being negative, conditioned on truly being negative. Arithmetically, this can also be defined in eq (xi) :
- $\mathrm{SN} = \frac{\text{no.of TPs}}{\text{no.of TPs+no.of FNs}}$ ……………… (xi)

  Here, eq (x) and (xi) define the TNs (true negatives); FPs (false positives); TPs (true positives); and FNs (false negatives).
- **The accuracy** of a test is its ability to distinguish the patient and healthy cases accurately. To evaluate the accuracy of a test, it should evaluate the proportion of

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TP and TN in all calculated cases. Arithmetically, this can also be defined in eq (xii):

- $\text{accuracy} = \frac{\text{no.of TPs+no.of TNs}}{\text{no.of TPs+no.of TNs+no.of FNs+no.of FPs}}$ ……………… (xii)
- The six-point rating scale (1 to 6) is developed based on the error % evaluated using eq (xiii) and shown in table 4. The rating is static as the extreme for the attribute with the lease error and vice versa.
- $\text{Error (\%)} = \left(\frac{\text{act}_{\text{value}} - \text{predict}_{\text{val}}}{\text{act}_{\text{val}}}\right) * 100$ …………………… (xiii)

Table 4. Rating Scale

Error (%ge)	Rating
<=10 percent	6 (best score)
Range: 11 to 20	5
Range: 21 to 40	4
Range: 41 to 60	3
Range: 61 to 80	2
>80 percent	1 (worst score)

Table 5. Proposed (SVOF-KNN) Recommender Model

Parameters	RMSE	MAE	Error Rate	SP	SN	Accuracy
Hybrid recommender model (SVOF-KNN)	0.4206	0.1218	0.1769	90.3043	91.3043	87.8

Table 5 discusses the RMSE, MAE, Error rate, SP, SN, and accuracy attained on the recommendation methods with the BCCDdatabase and data conception of SP, SN, accuracy, RMSE, MAE, and Error rate defined in figs 10 and 11.

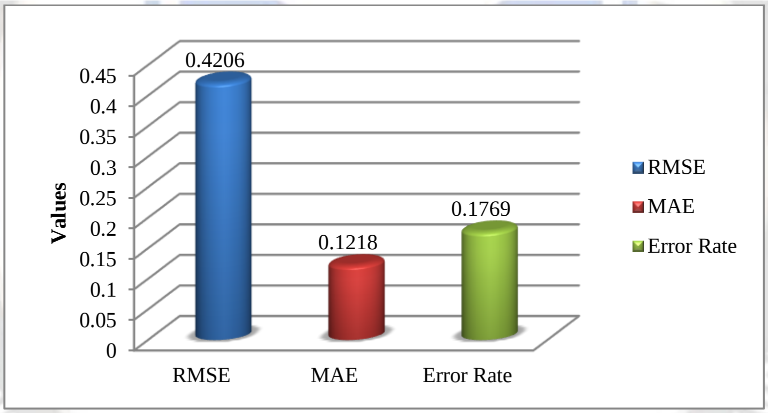

Figure 10. Performance metrics with Different types of Errors (MAE, RMSE, Error) in Hybrid recommender Model(SVOF-KNN)

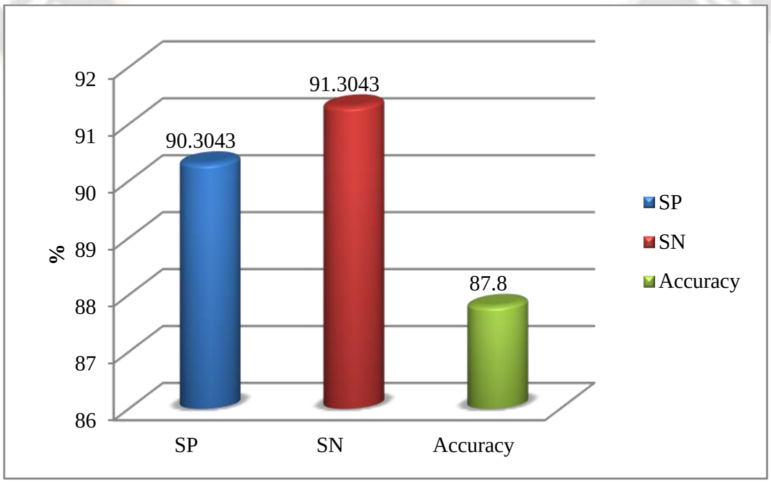

Figure 11. Performance metrics with different parameters (SP, SN, and accuracy) in Hybrid recommender Model (SVOF-KNN)

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We compared the outcomes of this investigation to other research that has made use of the equivalent BCCD database. Table 7 defines the assessment analysis of the findings between the research and existing research work with RMSE, MAE, Error Rate, SP, and SN rate.

b) *Comparative Analysis*:The comparison of the proposed hybrid recommender model (SVOF-KNN) classification methods with MLRS-BC model (KNNBasic), Baseline, SVD, SVM, and Extra-tress are defined in the form of RMSE, MAE, Error Rate, SP, SN, and accuracy rate performance parameters shown in table 6. All these calculation parameters play a significant role to attain an optimal and reliable classifier for the classification and recommendation system. Generally, the accuracy rate is measured as the best way to calculate the strength of a classifier.

Table 6. Comparison Analysis of the proposed recommender model with existing research works (RMSE, MAE, Error, SP, and SN)

Metrics	RMSE	MAE	Error Rate	SP	SN
Hyrbid recommender Model (SVOF-KNN)	0.4206	0.1218	0.1769	90.3043	91.3043
MLRS-BC model (KNNBasic)	0.4355	0.1969	0.1897	79.8	84.62
SVD	0.4206	0.1218	0.2	75	81.0
BaselineOnly	0.4355	0.1969	0.26	70.2	79.2
SVM and Extra Trees	0.4743	0.2128	0.1900	80.88	78.1

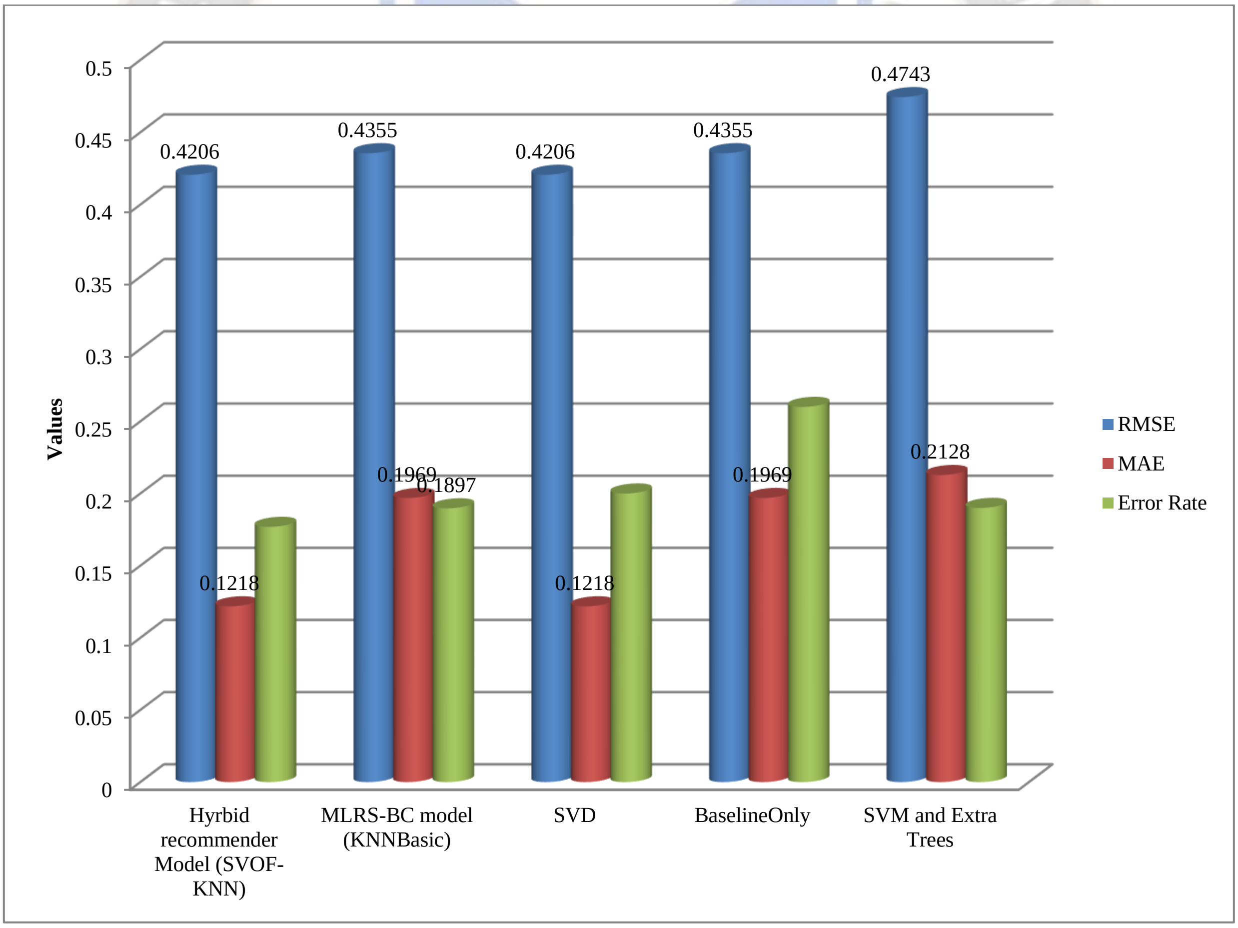

Figure 12. Comparison analysis proposed and existing models (Error, MAE, and RMSE) rate.

Table 6 defines the comparison analysis with research and previousmethods (Error, RMSE, MAE, SP, and SN) rate. Fig 12 and 13 define the comparison analysis with research and previousmethods with error rates and predicted values. The emphasized values in Table 7 show the minimum ER for the BC database attributes instances. The outcome

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indicates that the MLRS-BC model (KNNBasic), BaselineOnly, SVD, and hybrid recommender models have always formed a minimum ER for all the cancer cases and features of the BC database.

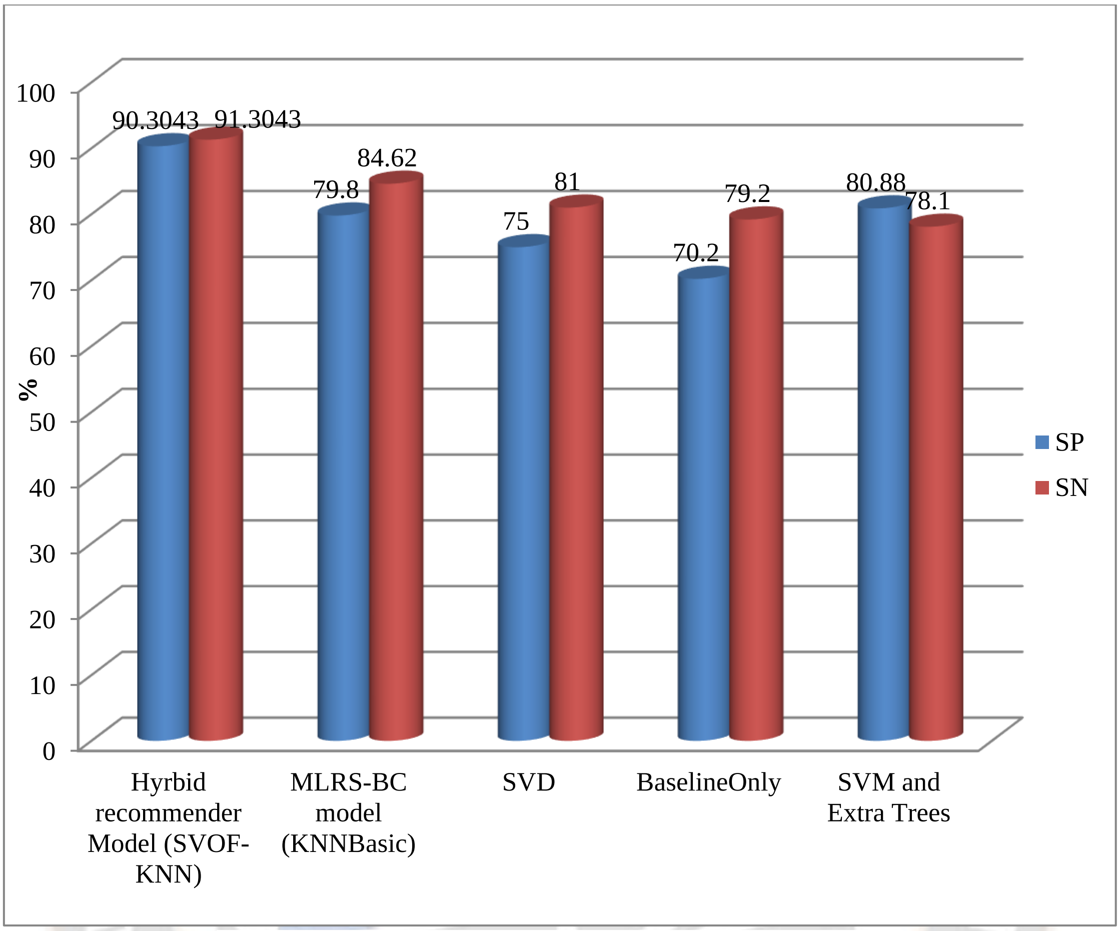

Figure 13. Comparison analysis proposed and existing models (SP and SN) rate.

After this evaluation, we compared the outcomes of this investigation to other research that has made use of a similar BCCD dataset. Table 7, and figure 14 define the comparative analysis of the findings between the research and previous research work with accuracy, SN, and SP rate.

Table 7. Comparison Analysis of the proposed recommender model with existing works: Accuracy rate, SN, and SP

Models/ Metrics	**Hybrid recommender model (SVOF-KNN)**	**MLRS-BC model (KNNBasic)**	**SVM and Extra Tree Model**
Accuracy (%)	87.8	80.3	78.7
SP (%)	90.3043	79.8	78.1
SN (%)	91.3043	84.61	80.8

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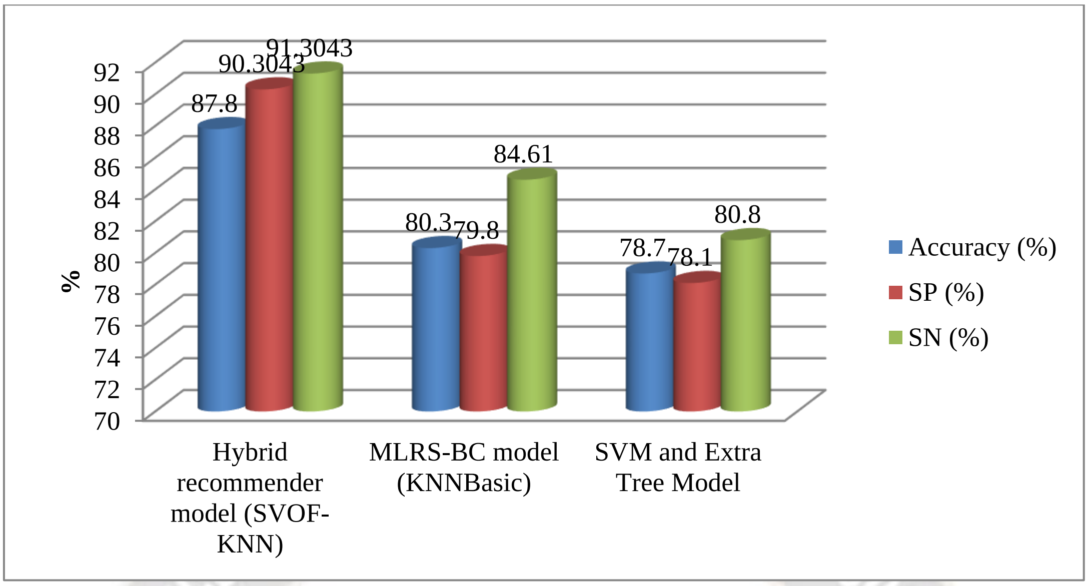

Figure 14. Comparison Analysis with hybrid recommender model(SVOF-KNN) with other existing models.

The proposed SVOF-KNN recommender model was associated with other data-driven methods to recommender BC using known risk parameters. The ML-based methods such as LR (logistic regression), MLP (multi-layer perceptron), DT (decision tree), KNN (k-nearest neighbor), RF(random forest), NB(naïve bayes), XGBoost (eXtreme gradient boosting), AdaBoost(adaptive boosting), SVM (support vector machine), were employed as BCC dataset prediction/recommender models. The metrics for model presentation are defined in table 5. The proposed model SVOF-KNN model was maximum accuracy, SP, and SN rates by up to 87.8%, 81.6%, and 82.6% resp shown in figs 16 and 17. The research model attained a 7 % average precision enhancement as compared with other BC recommender models shown in fig 15.

Table 8 Performance evaluations for BC recommender models

Methods	**Accuracy (%)**	**SP (%)**	**SN(%)**
MLP	66.8	66.4	66.6
LR	57.5	56.1	56.1
DT	67.9	70.0	67.8
NB	57.	59.7	59.7
RF	67.8	67.0	67.0
AdaBoost	74.0	73.4	73.4
XGBoost	75.0	74.3	82.6
SVM and Extra Tree	78.7	78.1	80.8
MLRS-BC model (KNNBasic)	80.3	79.8	84.6
Hybrid recommender (SVOF-KNN) Model	87.8	90.3	91.3

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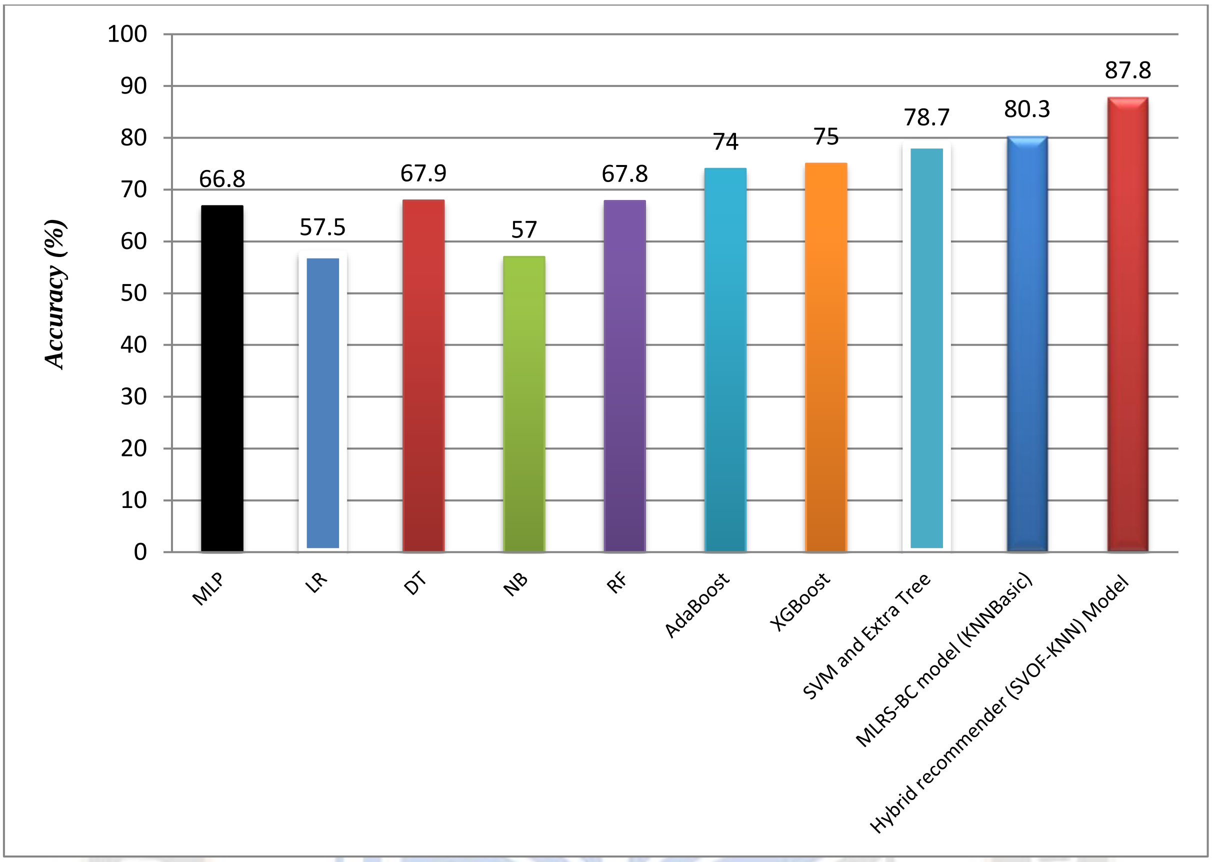

Figure 15. Accuracy Comparison of Hybrid recommender model (SVOF-KNN) with other methods

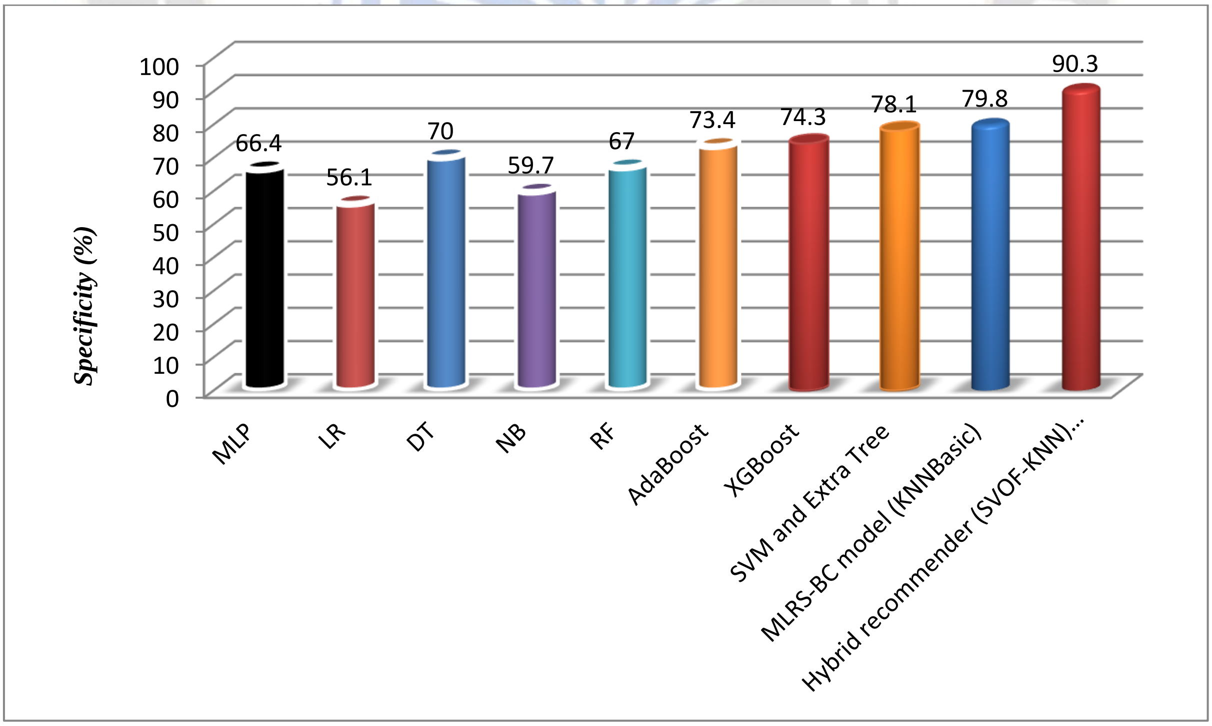

Figure 16. Specificity Comparison of Hybrid recommender model (SVOF-KNN) with other methods

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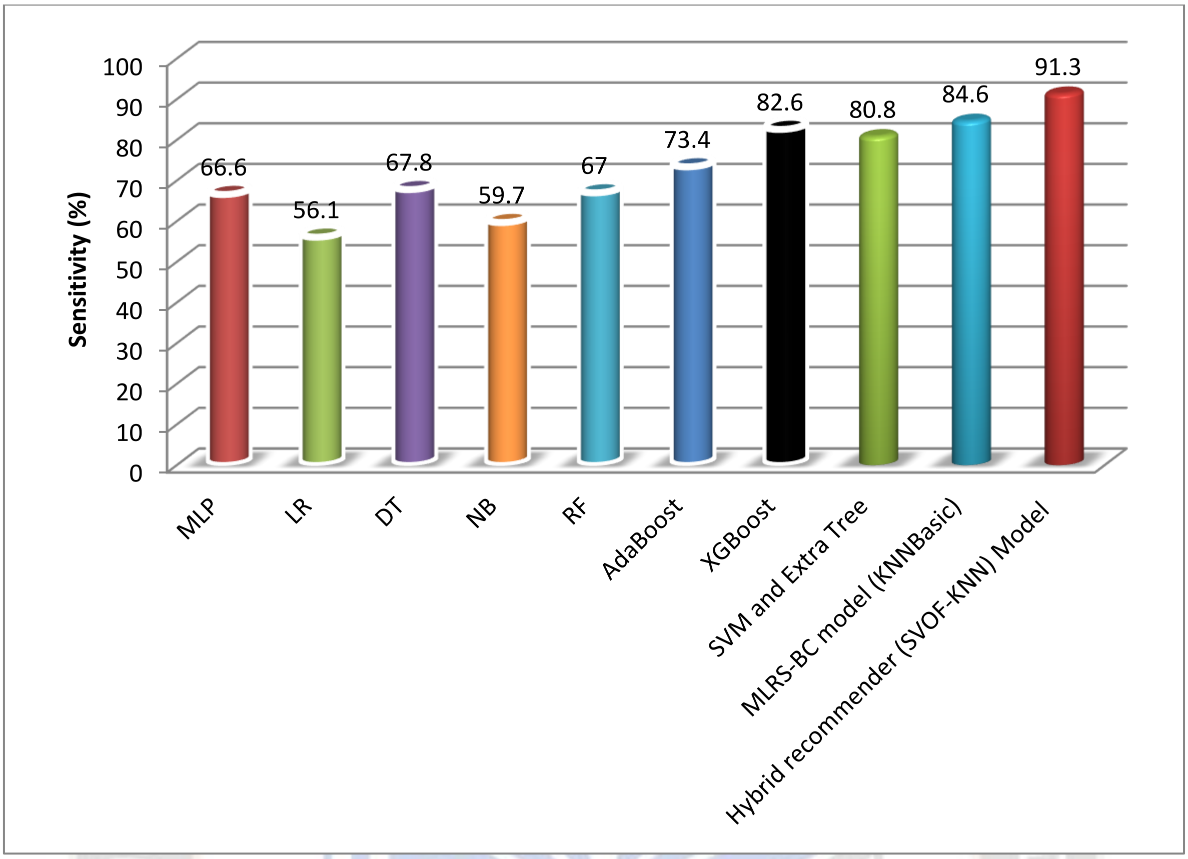

Figure 17.Sensitivity Comparison of Hybrid recommender model (SVOF-KNN) with other methods

VI. Conclusion and Future Scope

This proposed work reviews the three ML classification methods and RSs (recommender systems) developed for BC risk classification utilizingthe simulation analysis dataset BC Coimbra dataset. Various analyses were completed using the BC Coimbra dataset for BC classification. The Hybrid recommendation (SVOF-KNN) model represents a new plan for risk analysis (RA) and recommendationbased on the feature selection of the most important risk parameters using a correlation Heatmap matrix and exception value rates of forecast. So, this hybrid recommendation system allocates ratings using 6 scales for the instances or attributes. The simulation analysis consequences disclose that observable enhancement in the diagnosis and dependable attribute rating on the attributes are attained. These exploration outcomes would help to assess the threat of getting BC with each or multiple attributes without consisting ofa precision rate. This instrument can be preferably accepted for databases with several attributes too. This proposed work can additionally be augmented with the *.jpg database analysis to enhance its robustness on BC risk forecast.

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