# Performance Evaluation of Predictive Classifiers after Ensemble Feature Selection for Breast Cancer

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***Abstract*—Today many women all over the world suffer from a deadly disease called breast cancer. If this disease can be detected early then more is the chance of survival of the affected person. With the help of data mining and machine learning technique, this disease can be effectively predicted using the available relevant information. If the disease can be identified early then it can be cured efficiently by the health expert. In this paper two ensemble feature selection method namely MPLRFS and SVMFILEFS has been applied to the Wisconsin Breast Cancer diagnostic dataset (WBCD). The prediction of breast cancer is done on the WBCD dataset before and after the ensemble feature selection methods using four models like random forest (RF), Support Vector Machine (SVM), Logistic Model Trees (LMT) and Multilayer Perceptron (MLP). The performance evaluation of the models was done using confusion matrix indicators before and after the application of feature selection methods. The result obtained shows that the Multilayer Perceptron (MLP) classifier after the application of feature selection methods specifically after applying the SVMFILEFS than the MPLRFS on the dataset performed better for almost all the indicators. MLP classifier helps to effectively predict breast cancer than other classifiers which was used for the study. Later, a stacking ensemble model was applied on the attributes subset obtained after SVMFILEFS and MPLRFS. The meta-classifier random forest was able to make the prediction of breast cancer with better classification accuracy than MLP on SVMFILEFS applied dataset. The results of the experiment show that the proposed model is comparable to the other models on Wisconsin breast cancer dataset.**

***Keywords*—ensemble, feature selection, breast cancer, prediction, performance evaluation***

## I. INTRODUCTION

Breast cancer is one of the deadliest diseases commonly found in women all over the world. A lot of researches have been carried out by the health experts all over the world to identify the root cause of cancer. It has been found by researchers that the early detection and accurate diagnosis of the breast cancer can increase the survival rate of the disease affected women in the world. Today the online repositories contain a lot of diagnostic reports of several thousands of patients. But these online data may be prone to irrelevant data and noise. Hence, feature selection plays a vital role to predict the benign and malignant tumors. In this paper two different ensemble based feature selection methods namely SVMFILEFS [1] and MPLRFS [2] have been used on Wisconsin Breast Cancer diagnostic dataset (WBCD) [3] to select the best feature subset to be used for prediction. The prediction of breast cancer was done using four classifiers such as random forest (RF) [4], support vector machine (SVM) [5] [6], logistic model trees (LMT) [7] and multilayer perceptron (MLP) [8].

The research objective of this paper is to compare the performance of the classifiers on the WBCD dataset without feature selection and after applying the ensemble feature selection methods on it. The performance of the classifiers will be assessed by different evaluation metrics, including the classification accuracy, precision, recall, F-measure, sensitivity, specificity and ROC area. [9][10] The main aim of this study is to find the best classification model which can predict the breast cancer effectively.

The rest of the paper is organized as follows. Section II describes the ensemble feature selection methods. Section III presents the information about the dataset. Section IV presents the experimental results and Section V addresses the stacking ensemble classifier followed by the conclusion in section VI.

## II. ENSEMBLE FEATURE SELECTION METHODS

Mostly the downloaded datasets might contain some irrelevant attributes that is not significant to the predictive modelling problem. Such irrelevant attributes can be avoided by feature selection. Ensemble feature selection makes use of multiple feature selection methods and combines their normalized outputs to a quantitative ensemble importance. [11] In this paper two different ensemble feature selection methods are applied to the WBCD dataset. The details of the ensemble feature selection methods used for the study are described below:

### *A. MPLRFS*

MPLRFS [2] (Median [12], Pearson-Correlation [13], Logistic Regression [14] and Random Forest [15] – Feature Selection) is an ensemble feature selection method which was applied on the WBCD dataset to select the best attributes subset. MPLRFS was implemented using EFS package. [16] Each individual feature selection method may be highly biased but such biases can be compensated by an ensemble feature selection method. [11] It combines the subsets of attributes obtained from various feature selection methods. The results of each individual feature selection methods are normalized to a common scale, an interval from 0 to 1. Using EFS package, the feature selection methods such as median, Pearson-correlation coefficient, Logistic regression and random forest were selected to implement MPLRFS ensemble feature selection. The attributes selected using MPLRFS are concave_points_worst, area_worst, perimeter_worst, radius_worst, radius_se, texture_worst, area_mean, smoothness_worst, concave_points_mean, symmetry_worst, perimeter_mean, concave_points_se, fractal_dimension_worst, radius_mean and symmetry_mean.

## B. SVMFILEFS

SVMFILEFS [1] is a hybrid ensemble feature selection method that consists of two steps. In the first step, three filter based feature selection methods such as random forest filter [17], Chi-square filter [18] and information gain filter [19] were applied on the datasets. These filter methods apply a statistical measure to assign a scoring to each attribute. The filter methods were implemented using FSelector package. In the second step, SVMRFE [20] feature selection method was applied to the dataset after removing those selected attributes from the first step from it and the best top most attributes based on a threshold criteria was selected. The union of the attributes from the first and second step was considered for classification using various classification models such as random forest (RF), Support Vector Machine (SVM), Logistic Model Trees (LMT) and Multilayer Perceptron (MLP). The attributes selected using SVMFILEFS are perimeter_worst, area_worst, radius_worst, concave_points_worst, concave_points_mean, area_se, texture_worst, fractal_dimension_se, fractal_dimension_worst, concavity_mean and concave_points_se.

# III. DATASET

In this experiment, the dataset Wisconsin Breast Cancer Diagnostic (WBCD) was used for conducting the experiments. This dataset was downloaded from http://mlr.cs.umass.edu/ml/ datasets.html. [3]

# IV. EXPERIMENTAL RESULTS

## A. Performance Metrics

Performance metrics is used to determine how models can accurately make predictions, to make comparisons between different models and to assess the goodness of fit between model and data. Performance metrics are calculated using a predictive classification table called Confusion Matrix. In this research work, performance metrics such as accuracy, precision, recall, F-measure, sensitivity, specificity and ROC curve.

Accuracy is the percentage of correctly classified instances out of all instances. Precision [21] is which gives the fraction of relevant instances over the predicted samples. Recall [21] gives the ratio of correct samples over the actual ones. F-measure [21] gives the goodness of a classifier in the presence of rare classes and that trade-offs precision and recall. Sensitivity is the ability of a test to correctly classify an individual as 'having breast cancer'. [22] Specificity is the ability of a test to correctly classify an individual as 'not having breast cancer'. [22] Sensitivity refers to the true positive rate and Specificity refers to the false positive rate. ROC curve [10] is based on both sensitivity and specificity.

### 1) Dataset without Ensemble Feature Selection

The prediction of breast cancer was performed using WBCD dataset without applying any feature selection method. The prediction was done using four classifiers such as RF, SVM, LMT and MLP. The performance of the four classifiers were compared and assessed based on different performance measures such as accuracy, precision, recall, sensitivity, specificity and ROC. The performance of the classifiers based on accuracy without applying any feature selection on the dataset is shown in Table 1.

TABLE I. PERFORMANCE OF CLASSIFIER BASED ON ACCURACY WITHOUT APPLYING ANY FEATURE SELECTION METHOD

| CLASSIFIER | Without FS |
|---|---|
| RF | 95 |
| SVM | **97** |
| LMT | **97** |
| MLP | 96 |

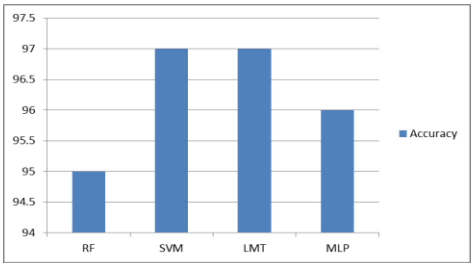


Fig. 1. Performance Evaluation of classifiers based on Accuracy

From the Figure 1, it is clear that the classifiers SVM and LMT performs better than the other classifiers based on accuracy.

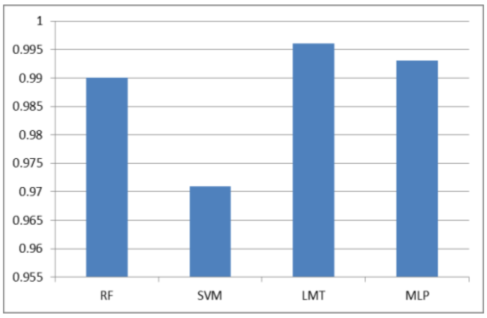


Fig. 2. Performance Evaluation of classifiers based on ROC

From Figure 2, it is found that the classifier LMT followed by MLP performs better than the other classifiers based on ROC.

TABLE II. COMPARISON OF CLASSIFIERS BASED ON SENSITIVITY, SPECIFICITY AND ROC AREA

| Performance Metrics | RF | SVM | LMT | MLP |
|---|---|---|---|---|
| Sensitivity | 0.958 | **0.977** | 0.972 | 0.967 |
| Specificity | 0.054 | **0.035** | 0.038 | 0.041 |
| ROC area | 0.990 | 0.971 | **0.996** | 0.993 |

From Table 2 and from the graph shown in Figure 3 , SVM classifier has the highest sensitivity value and the lowest specificity value. Though the LMT classifier has the highest ROC area, SVM classifier has a better performance based on sensitivity and specificity.

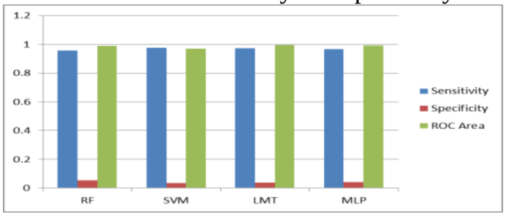


Fig. 3. Performance Evaluation of classifiers based on Sensitivity, Specificity and ROC

TABLE III. COMPARISON OF CLASSIFIERS BASED ON PRECISION, RECALL AND F-MEASURE

| Performance Metrics | RF | SVM | LMT | MLP |
|---|---|---|---|---|
| Precision | 0.958 | **0.977** | 0.972 | 0.967 |
| Recall | 0.958 | **0.977** | 0.972 | 0.967 |
| F-measure | 0.958 | **0.977** | 0.972 | 0.967 |

From Table 3 and from the graph shown in Figure 4, it is evident that the classifier SVM outperformed the other classifiers based on precision, recall and F-measure. Hence based on this analysis, the classifier SVM is a better predictor than the others, which is able to identify positive or negative conditions in patients who have or not breast cancer.

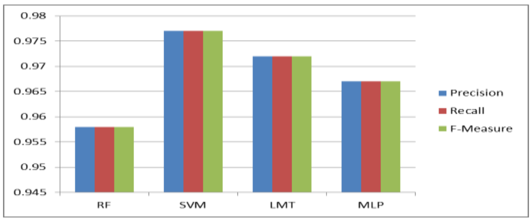


Fig. 4. Performance Evaluation of classifiers based on Precision, Recall and F-Measure

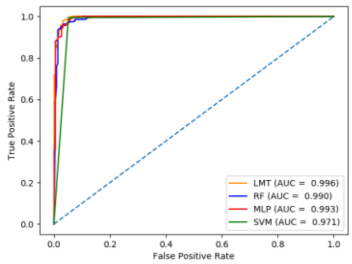


Fig.5. ROC curve of classifiers without feature selection

The Figure 5 shows the ROC curve of classifiers before applying any feature selection. Based on ROC, the LMT classifier shows the better performance than the others.

The evaluation of the performance of the models without feature selection revealed that the SVM Classifier outperformed the other classifiers in terms of indicators such as precision, recall, F-measure and sensitivity.

*2) Dataset with Ensemble Feature Selection*

Two different ensemble feature selection methods namely MPLRFS and SVMFILEFS were applied on the WBCD dataset to obtain the best attributes subset removing the irrelevant attributes. Then the best attribute subsets were used for predicting breast cancer using four classifiers such as RF, SVM, LMT and MLP. Later the performance of these classifiers was assessed using the same performance metrics such as accuracy, precision, recall, sensitivity, specificity and ROC. Table 4 shows the performance of classifiers based on accuracy after applying ensemble feature selection method.

TABLE IV. PERFORMANCE OF CLASSIFIER BASED ON ACCURACY AFTER APPLYING ENSEMBLE FEATURE SELECTION METHOD

| CLASSIFIER | With FS | |
|---|---|---|
| | **SVMFILEFS** | **MPLRFS** |
| RF | 97 | 96 |
| SVM | 97 | 97 |
| LMT | **98** | 97 |
| MLP | **98** | 97 |

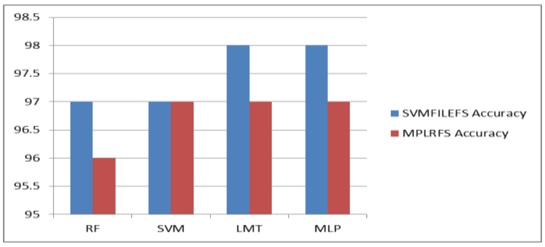


Fig. 6. Performance Evaluation of classifiers based on Accuracy

From Figure 6, it is found that the classifiers LMT and MLP shows better performance than the other two after SVMFILEFS ensemble feature selection. With the attribute subset obtained after MPLRFS feature selection, the classifiers SVM, LMT and MLP shows the better performance. But on comparing the accuracy obtained after the two ensemble feature selection methods, classifiers LMT and MLP achieved the highest accuracy with the attribute subset obtained after SVMFILEFS than the attribute subset obtained with MPLRFS ensemble feature selection.

TABLE V. COMPARISON OF CLASSIFIERS BASED ON SENSITIVITY, SPECIFICITY AND ROC AREA AFTER SVMFILEFS

| Performance Metrics | RF | SVM | LMT | MLP |
|---|---|---|---|---|
| Sensitivity | 0.965 | 0.968 | 0.970 | **0.975** |
| Specificity | 0.046 | 0.046 | 0.041 | **0.036** |
| ROC area | 0.991 | 0.961 | 0.993 | **0.993** |

Table 5 and Table 6 shows that the classifier MLP has the highest sensitivity and ROC area value and lowest specificity value. This is more clear from the graph shown in Figure 7.

TABLE VI. COMPARISON OF CLASSIFIERS BASED ON SENSITIVITY, SPECIFICITY AND ROC AREA AFTER MPLRFS

| Performance Metrics | RF | SVM | LMT | MLP |
|---|---|---|---|---|
| Sensitivity | 0.961 | 0.97 | 0.97 | **0.972** |
| Specificity | 0.048 | 0.045 | 0.039 | **0.038** |
| ROC area | 0.989 | 0.963 | 0.993 | **0.994** |

In terms of performance metrics such as sensitivity, specificity and ROC area, on comparing the performance of MLP classifier after the application of SVMFILEFS and MPLRFS, the performance of MLP classifier after SVMFILEFS is more better than the performance of MLP classifier after MPLRFS.

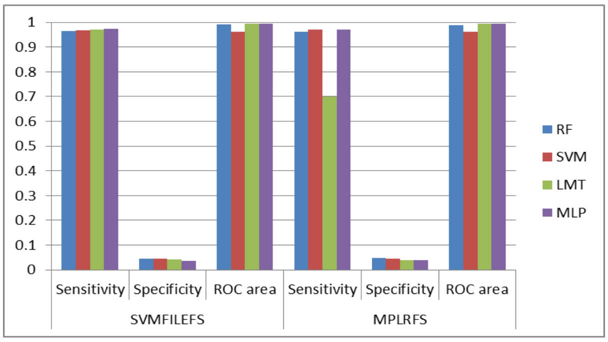


Fig. 7. Performance Evaluation of classifiers based on Sensitivity, Specificity and ROC Area

From Table 7 and Table 8 it is evident that the classifier MLP has the highest performance than the others based on Precision, Recall and F-measure after SVMFILEFS than MPLRFS.

TABLE VII. COMPARISON OF CLASSIFIERS BASED ON PRECISION, RECALL AND FMEASURE AFTER SVMFILEFS

| Performance Metrics | RF | SVM | LMT | MLP |
|---|---|---|---|---|
| Precision | 0.965 | 0.969 | 0.970 | **0.976** |
| Recall | 0.965 | 0.968 | 0.970 | **0.975** |
| F-measure | 0.965 | 0.968 | 0.970 | **0.975** |

TABLE VIII. COMPARISON OF CLASSIFIERS BASED ON PRECISION, RECALL AND FMEASURE AFTER MPLRFS

| Performance Metrics | RF | SVM | LMT | MLP |
|---|---|---|---|---|
| Precision | 0.961 | 0.971 | 0.97 | **0.972** |
| Recall | 0.961 | 0.97 | 0.97 | **0.972** |
| F-measure | 0.961 | 0.97 | 0.97 | **0.972** |

In terms of performance indicators such as precision, recall and F-measure, on comparing the performance of MLP classifier after the application of SVMFILEFS and MPLRFS, the performance of MLP classifier after SVMFILEFS is more better than the performance of MLP classifier after MPLRFS.

The Figure 8 shows the ROC curve of classifiers after applying SVMFILEFS feature selection. Figure 9 shows the ROC curve of classifiers after applying MPLRFS. Based on ROC, the MLP classifier (Area under ROC curve (AUC)=0.993) and LMT classifier (AUC=0.993) shows the better performance after applying SVMFILEFS and the classifier MLP (AUC=0.994) shows better performance than the others after applying MPLRFS. The performance evaluation of the classifiers based on ROC after applying SVMFILEFS and MPLRFS is shown in the graph in Figure 10.

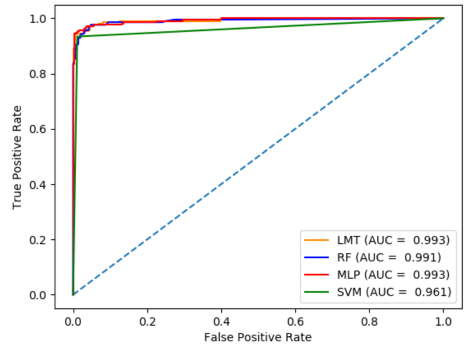


Fig. 8. ROC curve of classifiers after SVMFILEFS

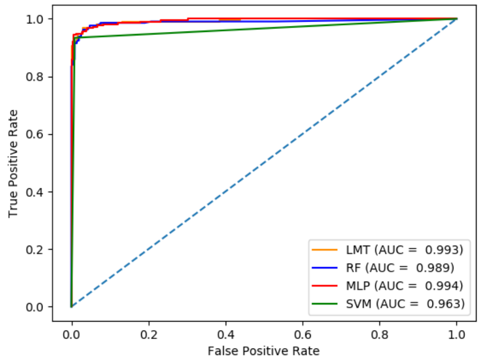


Fig. 9 ROC curve of classifiers after MPLRFS

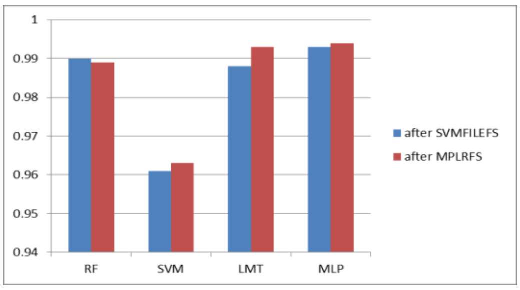


Fig. 10. Performance Evaluation of classifiers based on ROC after applying SVMFILEFS and MPLRFS

After the study of performance evaluation of the classifiers, it is noticed that MLP classifier has a significant better performance with regards to the indicators such as accuracy, precision, recall, F-measure, sensitivity, specificity and ROC area after SVMFILEFS than MPLRFS.

## V. STACKING ENSEMBLE CLASSIFIER

Next, in this paper a novel ensemble stacking method in which heterogeneous base classifiers were selected from a pool of base classifiers using SVFS [23] suitable for the SVMFILEFS and MPLRFS applied dataset. Then the selected base classifiers as shown in the Table 9 were used to form a stacking ensemble model which was then used for the prediction of breast cancer through meta-classifiers such as RF, SVM, LMT, MLP and J48. Table 10 and Table 11gives the classification accuracy and kappa value of the individual base classifiers with the SVMFILEFS and MPLRFS applied dataset.

TABLE IX. SVFS- CLASSIFIERS SELECTED FOR STACKING

| Feature Selection Method | Classifiers Selected for Stacking | | | | | | |
|---|---|---|---|---|---|---|---|
| SVMFILEFS | nb | rf | svm Radial | svm Linear weights | c5.0 | pda | knn |
| MPLRFS | knn | PART | treebag | lda | fda | Jrip | |

TABLE X. INDIVIDUAL BASE CLASSIFIERS WITH ACCURACY AND KAPPA AFTER SVMFILEFS ON WBCD

| Base Classifiers | Accuracy (%) | Kappa |
|---|---|---|
| Nb | 95.42 | 0.9021 |
| Rf | 96.54 | 0.9257 |
| svmRadial | **97.42** | 0.9448 |
| svmLinearweights | 97.3 | 0.9419 |
| c5.0 | 96.3 | 0.9204 |
| Pda | 96.19 | 0.917 |
| Knn | 91.44 | 0.8132 |

TABLE XI. INDIVIDUAL BASE CLASSIFIERS WITH ACCURACY AND KAPPA AFTER MPLRFS ON WBCD

| Base Classifiers | Accuracy (%) | Kappa |
|---|---|---|
| Knn | 93.3 | 0.8551 |
| PART | 94.9 | 0.8901 |
| Treebag | **96.4** | 0.9233 |
| Lda | 95.7 | 0.9046 |
| Fda | 96.1 | 0.9148 |
| Jrip | 94.9 | 0.8908 |

Table 12 gives the classification accuracy of meta-classifiers such as RF, SVM, LMT, MLP and J48 with the set of base classifiers obtained after applying the multistep stacking framework [24] on SVMFILEFS and MPLRFS applied WBCD dataset. It is clear from this table that Random Forest shows considerable improvement in classification than other meta-classifiers. The random forest classifier achieved 98.9% of maximum classification accuracy with the SVMFILEFS applied WBCD dataset and it was able to achieve 97.8% of classification accuracy with the MPLRFS applied WBCD dataset. RF classifier achieved the highest prediction accuracy with the both cases.

TABLE XII. CLASSIFICATION ACCURACY AND KAPPA VALUE OF THE META-CLASSIFIERS WITH SVMFILEFS AND MPLRFS APPLIED WBCD DATASET

| Meta-classifier | Ensemble FS | | | |
|---|---|---|---|---|
| | SVMFILEFS | | MPLRFS | |
| | Accuracy | Kappa | Accuracy | Kappa |
| RF | **98.9** | 0.9764 | **97.8** | 0.9525 |
| SVM | 91.8 | 0.8159 | 90.4 | 0.8095 |
| LMT | 98.7 | 0.9717 | 97.3 | 0.9416 |
| MLP | 97.7 | 0.9508 | 97.5 | 0.943 |
| J48 | 98.6 | 0.9701 | 97.2 | 0.9387 |

TABLE XIII. COMPARISON OF EXPERIMENTAL RESULTS OF PROPOSED METHOD AND OTHER PAPERS IN WBCD

| Author | Feature Selection used | Year | Ref : No: | Classifier | Accuracy (%) |
|---|---|---|---|---|---|
| Lavanya et al | FS methods in WEKA | 2011 | 25 | CART | 94.7 |
| Liu et al | FS_SFS | 2005 | 26 | SVM | 93 |
| Salama et al | GA | 2012 | 27 | fusion(SMO, IBK, NB and MLP) | 97.5 |
| Borges | InfoGain AttributeEval | 2015 | 28 | Bayesian Networks | 97.8 |
| | | | | J48 | 96.05 |
| Hazra et al | PCA , Pearson Corelation Coefficient | 2016 | 29 | NB | 97.39 |
| Aalaei et al | GA | 2016 | 30 | ANN | 96.7 |
| | | | | PS | 96.9 |
| | | | | GA | 96.6 |
| Djellali et al | FS_MRMR _SVM | 2016 | 31 | SVM | 97.81 |
| Latchoumi et al | no FS | 2017 | 32 | WPSO-SSVM | 98.42 |
| kavitha et al | SVMFILEFS | 2018 | our study | RF | 97 |
| | | | | SVM | 97 |
| | | | | **LMT** | **98** |
| | | | | **MLP** | **98** |
| | | | | **Stacking (rf meta_classifier)** | **98.9** |
| | MPLRFS | | | RF | 96 |
| | | | | SVM | 97 |
| | | | | LMT | 97 |
| | | | | MLP | 97 |
| | | | | **Stacking (rf meta_classifier)** | **97.8** |

Table 13 shows the comparison between classification accuracies of other published studies which used different feature selection methods and the accuracies obtained by our study on WBCD dataset. The meta-classifier random forest was able to achieve 98.9% of classification accuracy with the SVMFILEFS applied WBCD dataset which was quite better or nearly equal or comparable with other published works.

## VI. CONCLUSION

In this paper four classifiers such as Random Forest (RF), Support Vector machines (SVM), Logistic Model Trees (LMT) and Multilayer perceptron (MLP) were used on Wisconsin Breast Cancer Dataset (WBCD) to predict the presence of breast cancer in women. Performance comparisons of these classifiers were evaluated in detail using several performance indicators like accuracy, precision, recall, F-measure, sensitivity, specificity and ROC with and without the feature selection. The experimental results after prediction analysis showed that MLP classifier with 98% accuracy after applying SVMFILEFS is a more accurate model than the other classifiers used in this study. But when a stacking ensemble model was applied, it was found that the random forest meta-classifier was able to achieve much better prediction accuracy (98.9%) after applying SVMFILEFS than the other classifiers that were considered for this study.

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