

# Early Detection of Breast Cancer Tumors Using Linear Discriminant Analysis Feature Selection with Different Classification Methods

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## ABSTRACT

Globally, the frequency of breast cancer and its morality speak to a critical and developing risk for the developing countries. In Asia, Pakistan has the biggest rate of breast cancer. It is evaluated that every year 83,000 cases were reported in Pakistan and over 40,000 deaths are caused by breast cancer. Many Early identification of breast cancer can be achieved using data mining techniques, allowing preventative treatments to be done. Patients suffering from this malignancy have a better chance of surviving if they are diagnosed early. So, there is need to develop a system to diagnose breast cancer tumor at early stage. In this research WBCD and Duke Breast cancer dataset (DBDS) are used with Linear Discriminant Analysis (LDA) feature selection. Support Vector Machine (SVM), Decision Tree (DT), and Random Forest (RF) are classifiers to predict breast cancer tumors.

**Keyword:** Breast cancer, LDA, Feature selection, SVM, Decision Tree, WBCD, Duke Breast cancer

## 1. INTRODUCTION

Breast cancer is the prime reason of death in ladies. It is a multistage process that includes many cells and preventing it remains a challenge around the world. Early diagnosis is one of the most effective ways to prevent it. Because of early detection, the breast cancer survivors' 5-year relative survival score in some developing countries is over 80%.[1] Cancer begins in the cells, which are the primary cause of all structures and vital organs, including the breast, to develop. When the need for a body grows, cells in the body are further separated to create new cells. When regular cells are injured or get mature, they die and are replaced by new cells. This method may be unreliable at times. When a body does not need new cells, old or damage cells do not die. A lump, growth, or tumors is a mass of tissue formed by the development of extra cells.[2]

### 1.1 Breast cancer symptoms

- a) New chunk in the your breast
- b) Breast skin irritation
- c) Flaky skin in nipple section
- d) Pain in the vicinity of the breast
- e) Bloody nipple secretion in addition to breast milk
- f) variations in the breast's size, such as pulling upward or dimpled

### 1.2 Risk Factor

Anything that poses a "risk factor" is referred to as a "risk factor." that boosts your probability of growing breast cancer. Some factors can be controlled but some factors cannot be controlled. Controlled Factors are Weight, Diet, Exercise, Smoking, and Alcohol Consumption. Gender, age, family background, personal history of breast cancer, race, chest radiation therapy, pregnancy, and breastfeeding, reproductive history, and genetic mutations are all variables that cannot be control. Tumors formed as Benign or Malignant [3].

### 1.3 Clinical introduction

Cancer begins with cells, which are the fundamental components of all structures and organs in the body including the breast. When the need for a body grows, cells in the body are further separated to create new cells. When regular cells are injured or get mature, they die and are replaced by new cells. This method may be unreliable at times. When a body does not need new cells, old or removed cells do not die, as they should. A lump, growth, or tumors is a mass of tissue formed by the development of extra cells. Tumors formed as Benign or Malignant [4].

#### 1.3.1 Benign Tumor

The rule of a benign tumor is not destructive/ Harmful. Seldom, invade the tissues around them. A benign Tumor is not spread in the different body part. It can be eliminated and will not grow again.

### 1.3.2 Malignant Tumor

Malignant can create a danger to life. It has the ability to target nearby organs and tissues. It has the energy to grow to other areas of the body. Frequently can be expelled but in some cases develop back.

## 2. RELATED WORK

In past, many researchers worked on breast cancer tumor diagnosis and many techniques are used but still, a more accurate classification model is needed for detecting breast tumors that work with the combination of machine learning techniques. Previous work will be discussed in this section. In 2019 Gharibdousti with his team proposed a Hybrid Discriminant Logistic for reducing features model for predict breast cancer tumors. SVM, Nave Bayes, DT, LR, and ANN are applied to assess model results. The UCI Irvine repository's Wisconsin diagnostic repository is included. As a consequence, the Nave Bayes and SVM classification models outperform the competition. Of all versions, a model produced with a Hybrid DA-LR function range performs the best.[5] Aalaei et.al (2016) developed a wrapper approach model using a PS classifier and a GA for selecting features. The proposed feature selection method was applied to various classifiers, including ANN, PS, and GA-based classifiers. WBC and WPBC are the three data sets they use. The analysis shows that feature selection improve all classifiers' quality, consistency, and sensitivity.[6] Chaurasia (2018) developed a breast cancer survivability prediction model. Three of the most common data mining methods are used to create the prediction model Nave Bayes, RBF network, and J48. The 10 fold cross validation model was applied to diagnose results. With 97.36 percent accuracy, the result reveals that Nave Bayes is the best indicator. With 96.77 percentage points, RBF Network took second place. With a result of 93.41 percent, J48 came in eighth.[7] Akay (2009) to increase prediction accuracy uses a vector machine with a feature selection process. The WBCD is used to measure performance. The classification efficiency, positive negative predict value, specificity, ROC curves, and misunderstanding matrix are used to assess the model's results. The best accuracy is seen in the output is 99.51% obtained by the SVM model with it is compared with other classification models.[8] Bibhuprasad Sahu (2019) work on integrating artificial intelligence-based learning techniques with a multivariate statistical approach, a model was formulated. A hybrid feature selection method that combines PCA and ANN. Upon this WBCD is used, 10 fold cross-validations were used during the classification process. The proposed model classifies diagnosis cases into either cancerous or non-cancerous with a high amount of accuracy as compared with other existing models.[9] Joana Diz (2016) comparing the two datasets to detect the most accurate tools for predicting whether a tumors is benign or malignant. Texture matrixes were used to remove features, which were then categorized using DM algorithms. For the most part, RF is the best while NB was the best at identifying mass texture.[10] Chinnaiyan Ponnuraja (2017) Using data mining methods, we built a model to predict patient survival. The DT algorithm employs defined features. The DT algorithm yields a path with the best rate of survival (96.4%) and the highest rate of dying (96.4%).[11] Uma Ojha (2017) Compare Clustering and Classification Algorithm on Dataset (DT, SVM, Fuzzy c-mean). The experiment of classification algorithms are best prediction model than the clustering algorithm. According to the findings, the DT and SVM have the best prediction model with 81% accuracy and fuzzy c-mean with the low accuracy with 37%. [12] Emina (2017) developed a model for breast cancer detection. The extraction of insightful and important features is done using genetic algorithms. In the second level, different human and multiple classification models were examine to build an effective source for breast cancer classification. The RF model with GA most accurate with 99.48%. [13] Seral Sahana (2007) suggested a novel mixed algorithm for breast cancer detection based on a fuzzy artificial immune system and the KNN algorithm. The WBCD was used to develop a tool for solving this diagnosis issue. As contrasted to other research, In terms of classification precision, our suggested method outperforms them. The best classification accuracy ever achieved was 99.14 percent. Using 10-fold cross-validation, the classification accuracy was determined.[14] Yılmaz kaya (2013) Centered on a rough system and an intense learning engine, a breast cancer detection with a new intelligent classification has been suggested. Breast cancer was diagnosed using a combination of rough collection (RS) and extreme learning machine (ELM) approaches. For research, the WBCD was used. The RS + ELM model was found to have a 100 percent success rate.[15] F. M. Okikiola (2019) proposed a fuzzy specialist framework for breast cancer diagnosis and treatment recommendations. The JAVA, MATLAB, and the SQLite database were used to create the framework. The fuzzy inference was used to increase the system's accuracy and precision improve 0.1 % according to the assessment. The method is simple to use and has a high degree of validation.[16] Perviz Abdulmaleki (2001) ANN was used to propose a classification model with extraction of features for breast cancer with resonance imaging. The Jackknife approach was used to plan, network train, and test a neural network system and compared with Radiologists. The diagnostic accuracy of this network is 89% compared with radiologists' 79%. [17] Carlos Andres (1999) proposed a fuzzy genetic approach to diagnose breast cancer by Fuzzy processes and evolutionary algorithms are combined in this study. The fuzzy-genetic approach produces systems that attain high classification performance and involve a few simple rules.[18] Sabri Boughorbel (2016) AU ROC accuracy for various diagnose times was used to assess the performance of many prediction strategies for breast cancer prognosis.

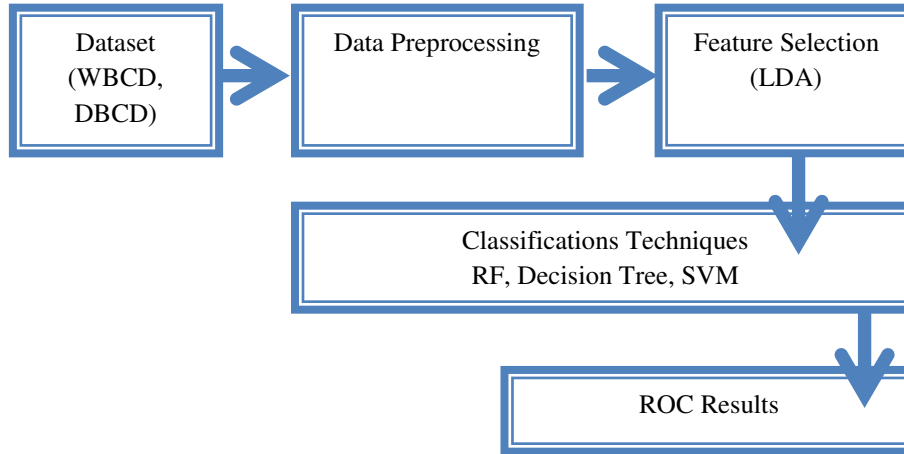
SVM, RF, ANN, KNN, and Boosted Trees are contrasted to the GLM, GLM-Net, PLS, SVM, RF, Neural Networks, KNN, and Boosted Trees.[19] Pakizah Saqib (2019) proposed a range of hybrid features approach with the aim of generating the most appropriate feature and improving result prediction. A wrapper is used, which consists of a GA, a heuristic search function, and a RF forecasting model. The proposed method was tested on the WBCD, and it achieved a prediction accuracy of 99.04 percent.[20] Davi Carvalho (2016) proposed a hybrid approach to aid in breast cancer early detection. A Bayesian Network is built hybrid method to measure the conditional the likelihood of a certain person developing cancer, and MCDA is used. Automated develop a tool to provide a precise detect in events in general and to assist in the decision-making process in more complex cases.[21] Zohaib Mushtaq (2019) explores the efficiency of KNNs by experimenting with K values and distance function order to find an effective KNN. Chi-square-based feature selection, feature selection without a SVM, feature selection without a SVM The findings showed that, as opposed to current versions, the Chi square based feature selection methodology has the highest accuracy levels.[22] Reem Alyami (2017) ANN SVM and along with feature extraction was used to propose a model for diagnosing breast cancer. SVM and ANN are used to pick features depending on the correlation coefficient. In observational experiments comparing SVM and ANN, the results showed that SVM performed well compared ANN with classification precision of 97.14 and 96.71, respectively.[23] T.Sridevi (2014) proposed a hybrid model K-mean clustering and SVM on WBCD. SVM is examine to partition the given information system using the K means clustering algorithm. A hybrid model's performance rate is calculated by 99 percent.[24] Cuong Nguyen (2013) proposed a machine learning system built on a RF classifier with feature selection for diagnosing and prognosticating breast cancer. A model proposed by merging RF and method of selecting features. In the best-case scenario, accuracy of classifier is 100 percent, with an average of 99.8%.[25] Abeer Alzubaidi (2016) proposed a model to diagnose breast cancer through GA and mutual information. GA based on the MI technique with two classification model, namely the KNN, and SVM. The proposed model perform well when it both these model are combined.[26] Dr.J.Arunadevi (2019) GLM and RF used Feature selection three classifiers KNN, SVM, and ANN are also examine to detect breast cancer. As a result feature selection method improves the accuracy of the classification model. GLM performed very well as compared to other model.[27] Abderrahmane Eddy (2020) for the classification of breast cancer, affiliation rules and help vector machines are used on a reduced feature set. To exclude trivial features, Association Rules (AR) is used. To separate the incoming tumors, multiple classifiers are used in the second step. For eight attributes, the SVM model with AR 98.4 % which is best among all classification while for four properties it is 96.14 percent.[28] Adel S Assiri and Saima Nazir (2020) focused on a plurality voting system, suggested an ensemble classification mechanism. LR learning, SVM learning with gradient descent optimization, and multilayer networks are used in ensemble classification with a voting system. The WBCD (Wisconsin Breast Cancer Dataset) is used. The majority-based voting mechanism outperforms the state-of-the-art WBCD algorithm with a score of 99.42 percent.[29] Ahmed Abdullah (2020) developed a hybrid feature selection technique that blends the benefits of feature selection methods with an optimized OGA to choose the right features for results improvement. As a fitness function, the C4.5 DT classifier is used. The output is that for optimal feature collection, Single filter methods and PCA are outperformed by the proposed hybrid feature selection.[30]

### 3. PROPOSED FRAMEWORK

The publically available WBCD from UCI Repository and Duke Breast cancer dataset are used. LDA feature selection with different Classifiers to predict Breast cancer. SVM, DT, and RF classifiers are used in this prediction model.

#### 3.1 Data Preprocessing

Data collection is an important component of Research. In this research, WBCD is used for the diagnosis of breast cancer tumors. The dataset is gathered from UCI Repository which is publically available on the Internet. Second Dataset Duke Breast cancer dataset is available on kaggle website. WBCD dataset consist of 699 records and each record has 9 attributes. Each feature value range is 1-10. The target variable is 0 and 1, 0 for benign tumors and 1 for malignant tumors. Second dataset is used in this research is duke breast cancer. DBCD is developed by Shirish Krishnaji Shevade and S. Sathiya Keerthi in 2003. Dataset is publically available at LIBSVM (Library for SVM) Data repository. Dataset consist of 86 instances and 7130 attributes. The dataset contain zero missing value. Class distribution value is 0 and 1. The whole process is illustrated in Figure 1.



**Figure 1:** Breast Cancer Tumors Classification (BCTC) Model

### 3.2 Feature Selection

In this research R, 4.0.3 is used. LDA feature selection is used in R to select a feature from WBCD. Feature selection a machine learning technique which is used to select the relevant feature and ignore irrelevant feature for better accuracy of a model. Every feature selection technique defined attributes of a dataset into two groups firstly is the relevant feature and secondly is the irrelevant feature. In this research LDA feature selection method is used for the detection of breast tumors.

$$P(X|\pi_i) = 1/(2\pi)^{p/2} \exp[-1/2(X - \mu_i)^T \Sigma^{-1}(X - \mu_i)] \quad [1]$$

### 3.3 Machine Learning Techniques

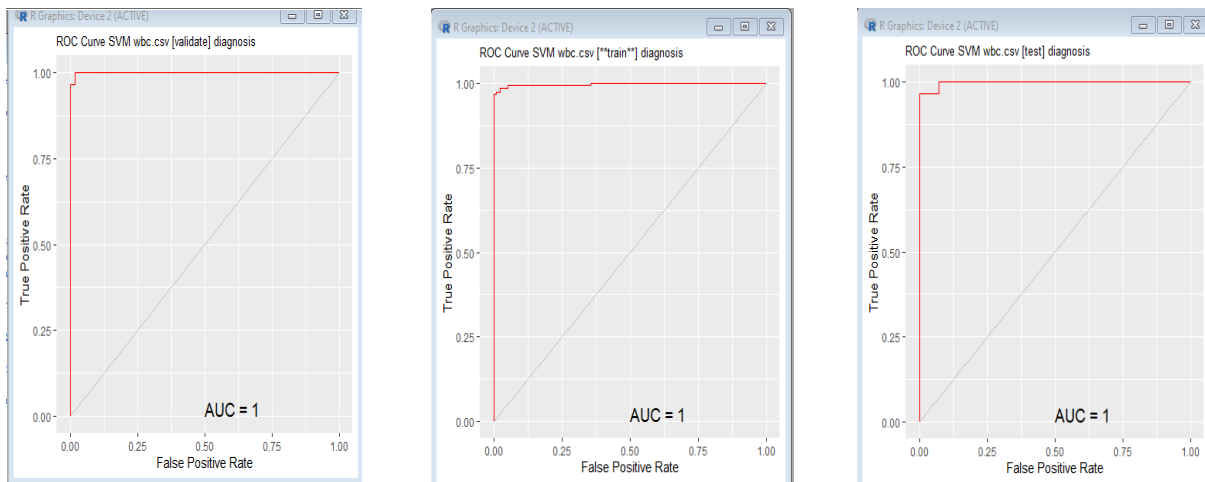
After preprocessing and feature selection from WBCD and DBCD, now Machine learning classifiers are applied to the data to predict tumors. SVM, DT, and RF Classifiers are applied.

## 4. RESULTS AND DISCUSSION

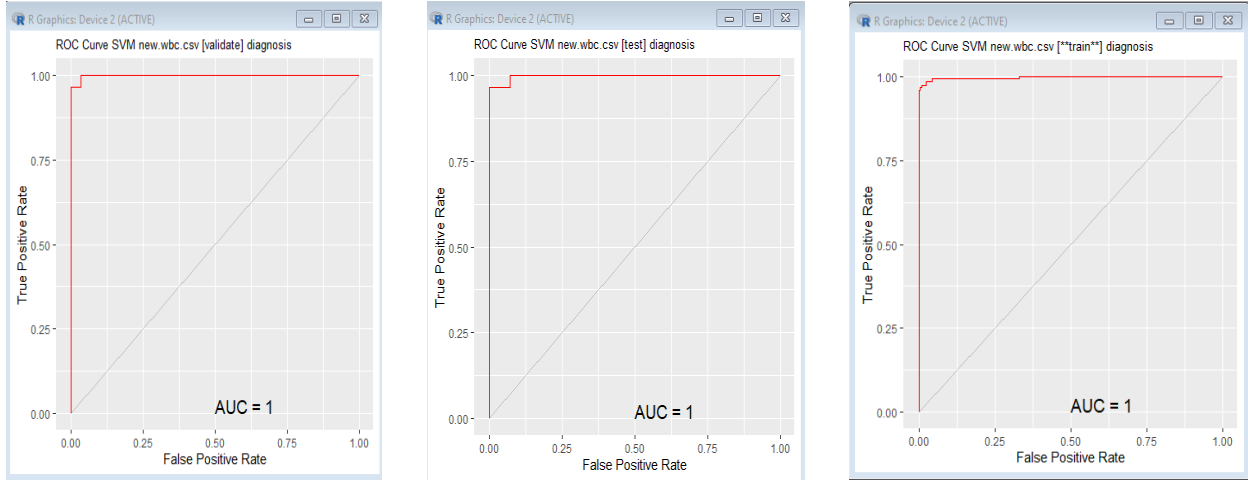
Results are calculated on two datasets. WBCD and DBCD are used.

### 4.1 Wisconsin Breast Cancer Dataset (WBCD)

We are using R 4.0.3 software for classification. Features are selected through LDA which is also implemented in R. SVM, DT, and RF classification is applied on the dataset. These models are used for training, testing, and validation. Firstly SVM model is implemented. ROC curves obtained on SVM model without LDA are depicted in Figure 2 whereas Figure 3 illustrated ROC curve on SVM model with LDA respectively.



**Figure 2:** ROC Curve on SVM Model without LDA on WBCD dataset



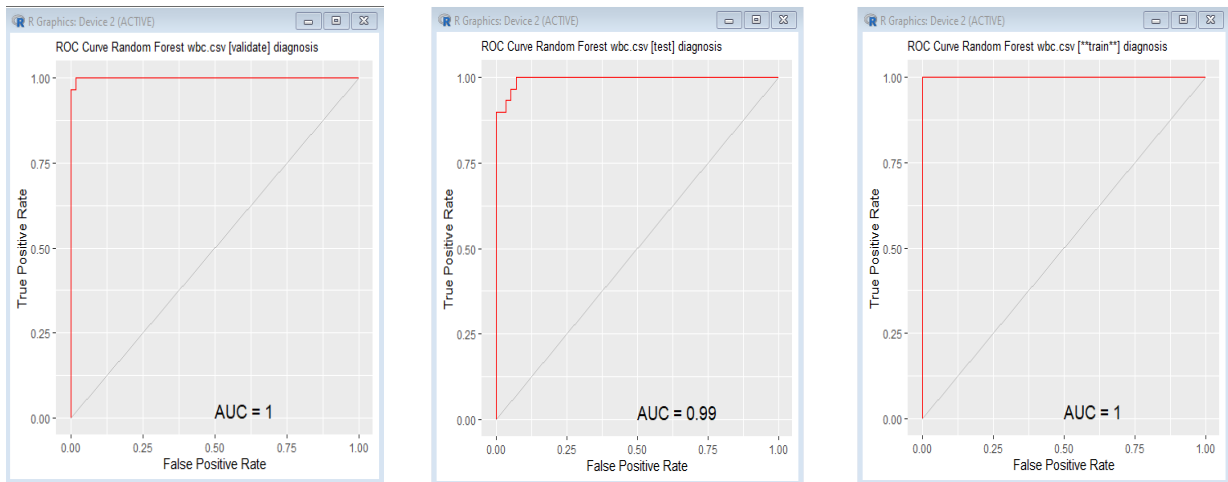
**Figure 3:** ROC Curve on SVM Model with LDA on WBCD dataset

Table 1 illustrated classification results of WBCD with and without LDA.

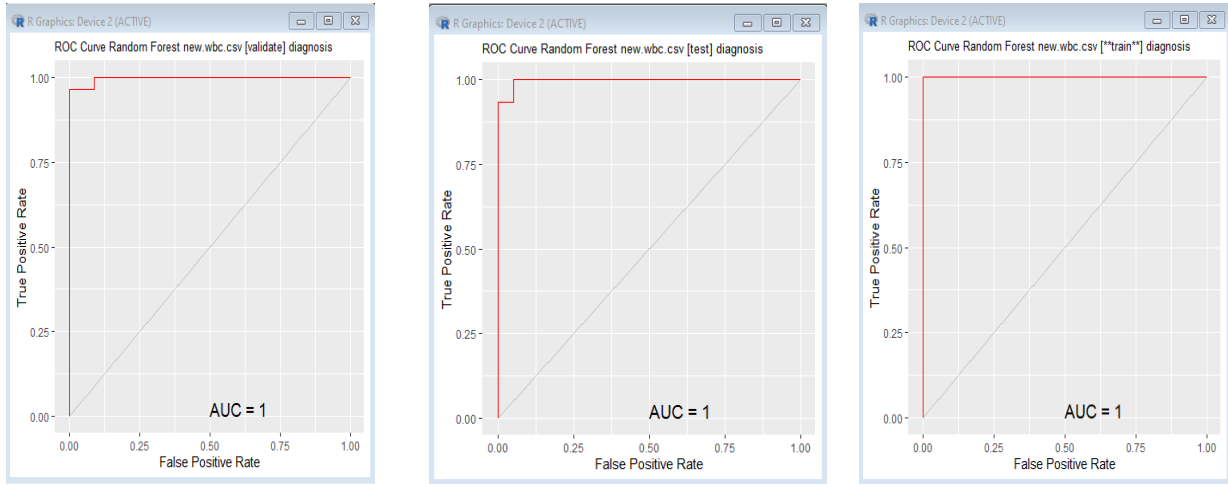
**Table 1:** Classification Results using SVM with LDA and Without LDA

| Dataset          | Classification Model | Time Taken (Seconds) | Training (ROC) | Testing ( ROC) | Validation (ROC) |
|------------------|----------------------|----------------------|----------------|----------------|------------------|
| WBCD without LDA | SVM                  | 1.08                 | 0.9970         | 0.9976         | 0.9994           |
| WBCD with LDA    | SVM                  | 0.11                 | 0.9971         | 0.9976         | 0.9988           |

At the second step, ROC curves of Random Forest without LDA (Figure 4) whereas with LDA (Figure 5) on Training, Testing, Validation.



**Figure 4:** ROC Curve on RF Model without LDA on WBCD dataset



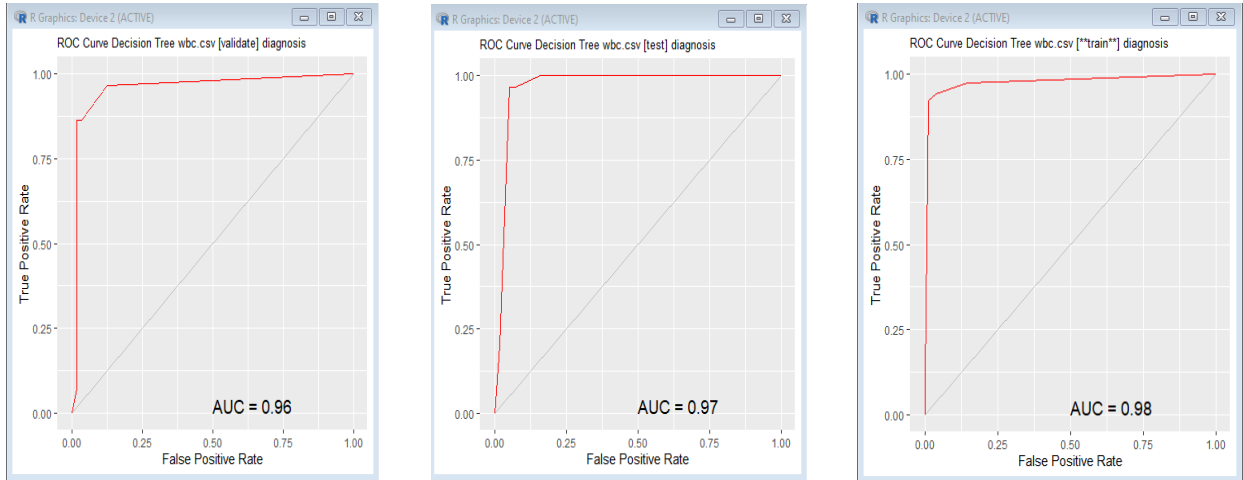
**Figure 5:** ROC Curve on RF Model with LDA on WBCD dataset

Table 2 illustrated classification results of WBCD using RF with and without LDA.

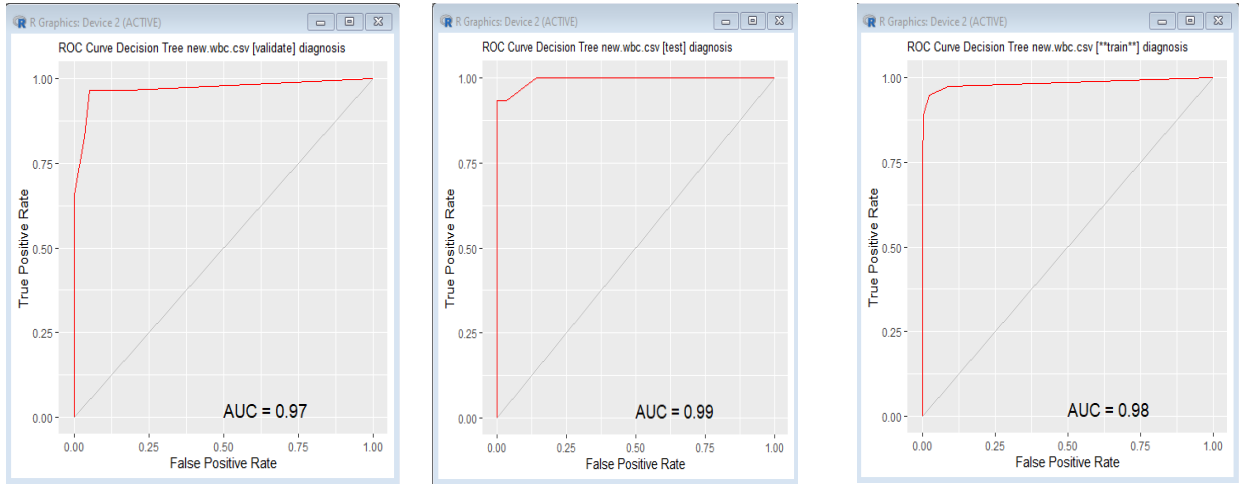
**Table 2:** Classification Results using RF with LDA and Without LDA

| Dataset          | Classification Model | Time Taken (Seconds) | Training (ROC) | Testing (ROC) | Validation (ROC) |
|------------------|----------------------|----------------------|----------------|---------------|------------------|
| WBCD without LDA | RF                   | 0.84                 | 1.0000         | 0.9946        | 0.9994           |
| WBCD with LDA    | RF                   | 0.33                 | 1.0000         | 0.9964        | 0.9969           |

ROC curves using DT model without LDA and with LDA is illustrated in Figure 6 and Figure 7 respectively.



**Figure 6:** ROC Curve on DT Model without LDA on WBCD dataset



**Figure 7:** ROC Curve on DT Model with LDA on WBCD dataset

Table 3 illustrated the classification results of DT model with LDA and without LDA

**Table 3:** Classification Results using DT with LDA and Without LDA

| Dataset          | Classification Model | Time Taken (Seconds) | Training (ROC) | Testing (ROC) | Validation (ROC) |
|------------------|----------------------|----------------------|----------------|---------------|------------------|
| WBCD without LDA | DT                   | 0.08                 | 0.9765         | 0.9670        | 0.9575           |
| WBCD with LDA    | DT                   | 0.04                 | 0.9831         | 0.9940        | 0.9704           |

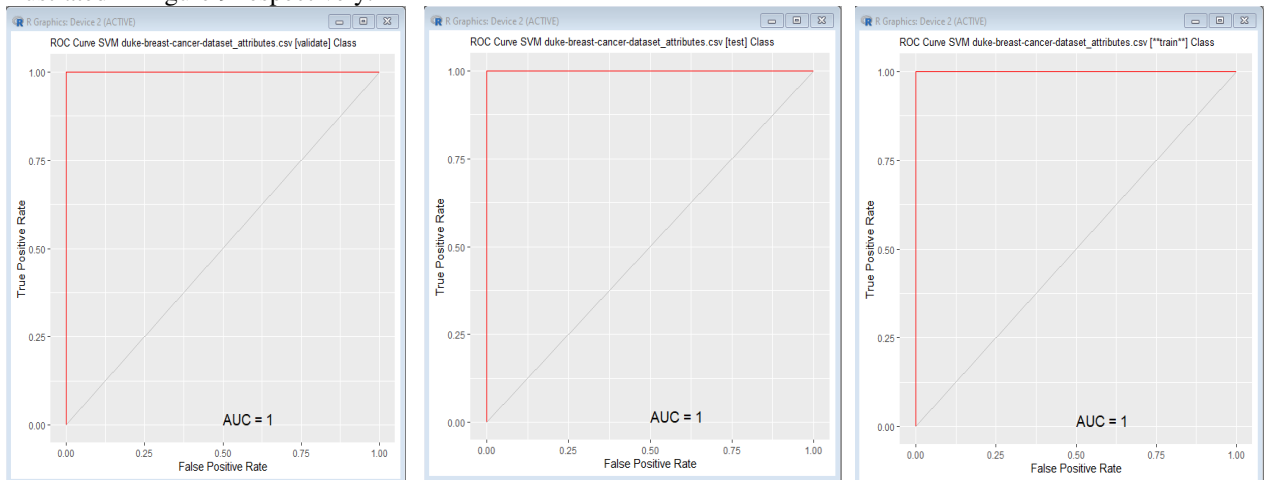
These are the results of different machine learning classification techniques with LDA with without LDA feature selection.

#### 4.2 Duke Breast Cancer Dataset (DBCD)

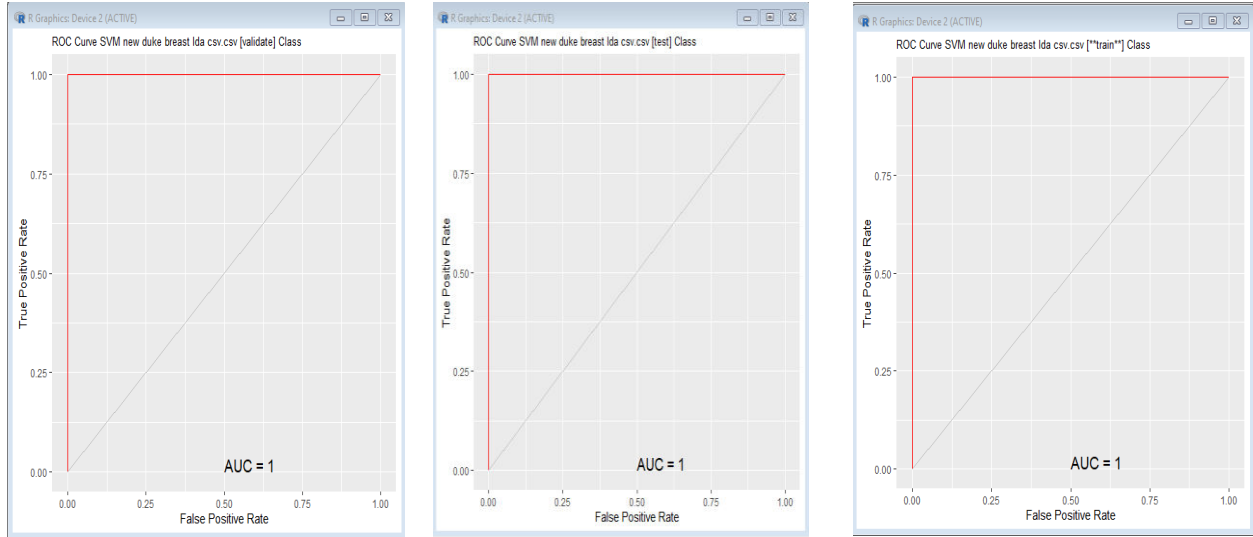
Second dataset is used in this research is duke breast cancer. DBCD is developed by Shirish Krishnaji Shevade and S. Sathya Keerthi in 2003. Dataset is publically available at LIBSVM (Library for SVM) Data repository. Dataset consist of 86 instances and 7130 attributes. The dataset contain zero missing value. Class distribution value is 0 and 1.

##### 4.2.1 SVM Model

ROC cure without LDA on SVM model using DBCD dataset is depicted in Figure 8, whereas with LDA is illustrated in Figure 9 respectively.



**Figure 8:** ROC Curve on SVM Model without LDA on DBCD dataset



**Figure 9:** ROC Curve on SVM Model with LDA on DBCD dataset

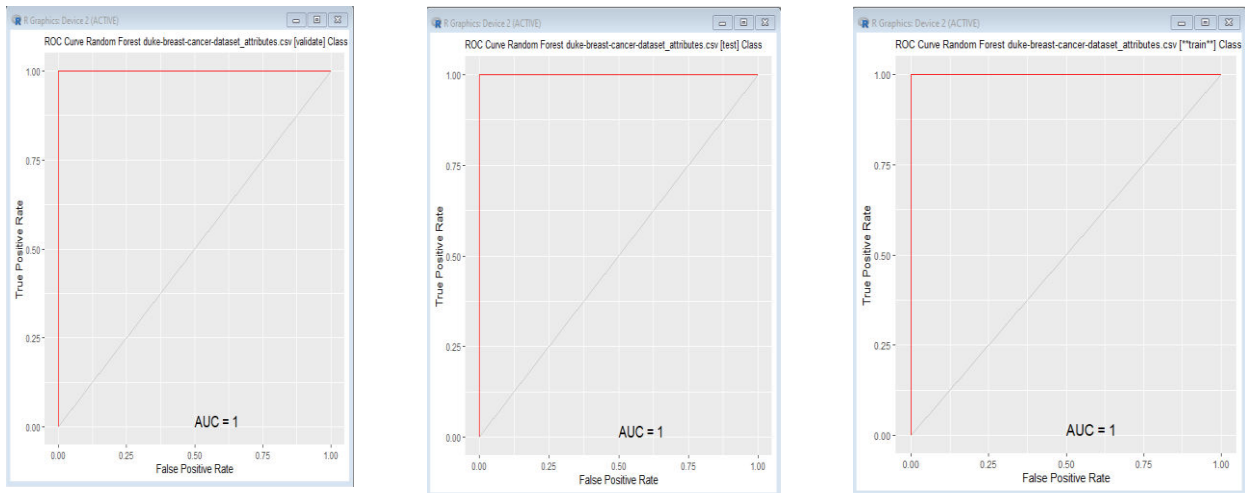
The results of SVM model on DBCD with LDA and without LDA is shown in Table 4.

**Table 4:** Classification Results using SVM with LDA and Without LDA

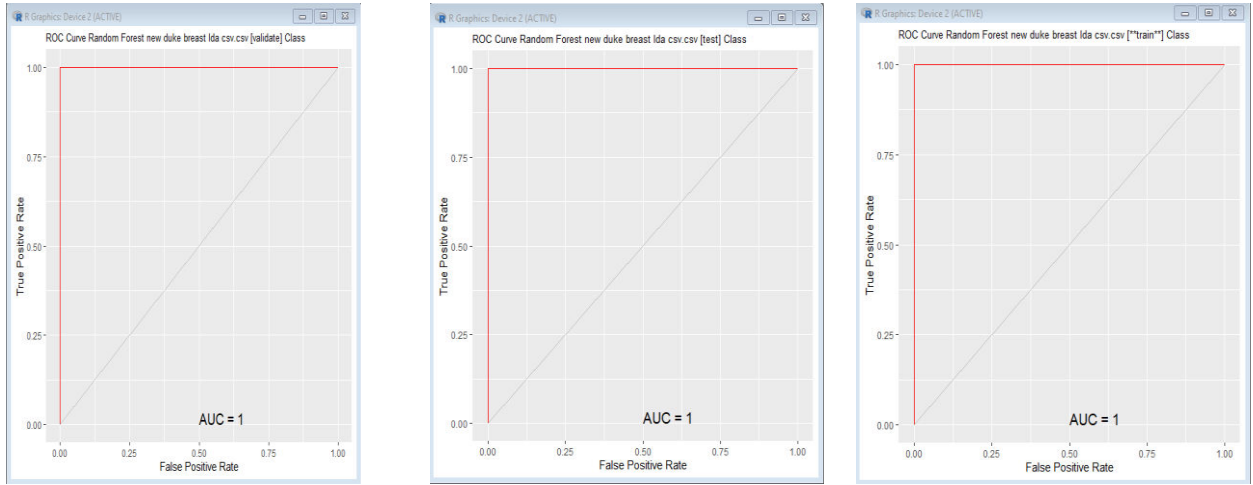
| Dataset          | Classification Model | Time taken (Seconds) | Training (ROC) | Testing (ROC) | Validation (ROC) |
|------------------|----------------------|----------------------|----------------|---------------|------------------|
| DBCD without LDA | SVM                  | 7.16                 | 1.0000         | 1.0000        | 1.0000           |
| DBCD with LDA    | SVM                  | 1.75                 | 1.0000         | 1.0000        | 1.0000           |

#### 4.2.2 Random Forest

ROC curve without LDA on RF model using DBCD dataset is depicted in Figure 10, whereas with LDA is illustrated in Figure 11 respectively.



**Figure 10:** ROC Curve on RF Model without LDA on DBCD dataset



**Figure 11:** ROC Curve on RF Model with LDA on DBCD dataset

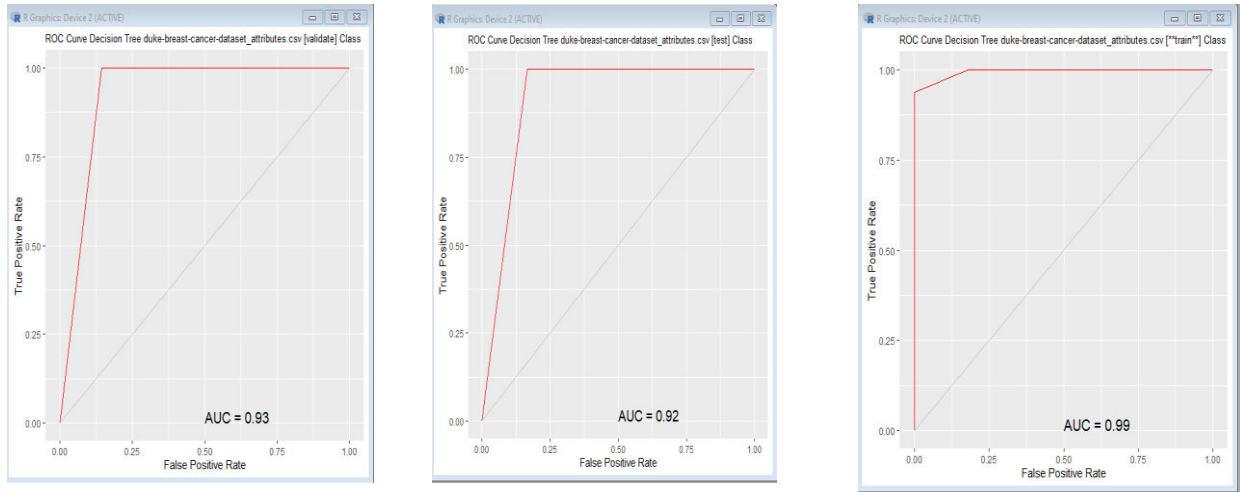
The Results of Random Forset with LDA and without LDA on DBCD is depicted in Table 5.

**Table 5:** Classification Results using RF with LDA and Without LDA

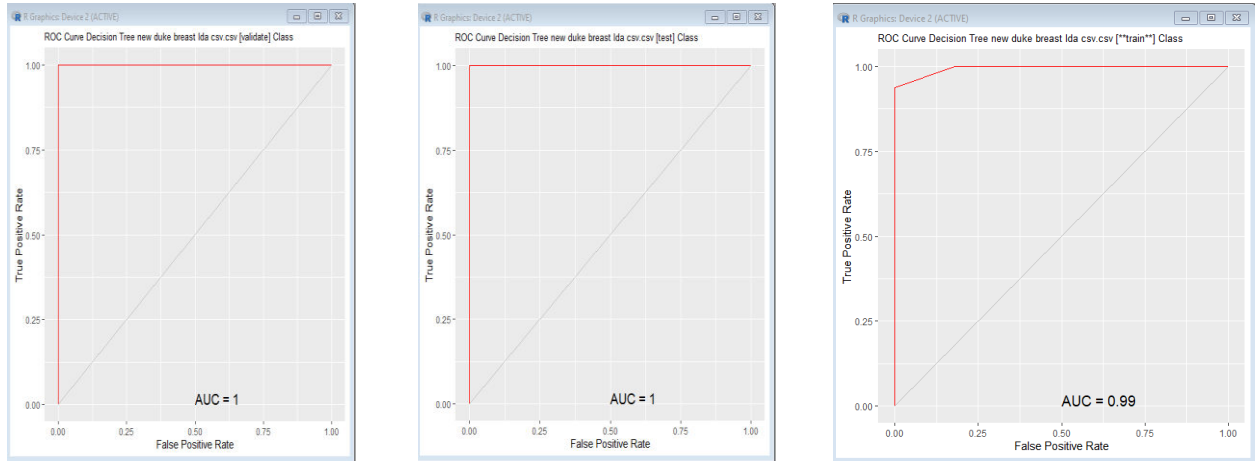
| Dataset          | Classification Model | Time taken (Seconds) | Training (ROC) | Testing (ROC) | Validation (ROC) |
|------------------|----------------------|----------------------|----------------|---------------|------------------|
| DBCD without LDA | RF                   | 41.56                | 1.0000         | 1.0000        | 1.0000           |
| DBCD with LDA    | RF                   | 1.55                 | 1.0000         | 1.0000        | 1.0000           |

#### 4.2.3 Decision Tree

ROC cureof Decision Tress without LDA model using DBCD dataset is depicted in Figure 12, whereas with LDA is illustrated in Figure 13 respectively.



**Figure 12:** ROC Curve on DT Model without LDA on DBCD dataset



**Figure 13:** ROC Curve on DT Model with LDA on DBCD dataset

The Results of DT with LDA and without LDA on DBCD is highlighted in Table 6.

**Table 6:** Classification Results using DT with LDA and Without LDA

| Dataset          | Classification Model | Time taken (Seconds) | Training (ROC) | Testing (ROC) | Validation (ROC) |
|------------------|----------------------|----------------------|----------------|---------------|------------------|
| DBCD without LDA | DT                   | 4.72                 | 0.9944         | 0.0167        | 0.9286           |
| DBCD with LDA    | DT                   | 0.17                 | 0.9944         | 1.0000        | 1.0000           |

## 5. CONCLUSION

In this thesis, two dataset are used for classification without feature selection and with feature selection. Two dataset are WBCD and Duke Breast Cancer Dataset. In first experiment different classification techniques like SVM, DT and RF are implemented without feature selection method. These models provide higher accuracy rate almost 1.0000 at training, testing, and validation. But the Issue is that these entire models spend more time for execution. To reduce the time LDA feature selection is applied to select positive feature. After selecting these feature classification method implemented. This feature selection reduces more than half time. After developing this LDA model one more dataset is used to check the entire working of the model. Duke breast cancer dataset is used for second dataset. Similarly, as in previous experiment this dataset is used with feature selection and without feature selection. This dataset is more complex than previous one because this dataset have 7130 attributes. Its take a lot of times to load in rattle. Its structure is complex and taking a lot of time to run classification model. This dataset on these classification models performed well on training, testing and validation. But the problem is that it's taking a lot of time to execute. The proposed model is implemented on that dataset to select positive features. After selecting these feature 80% time is reduced in all classification model. Different feature selection and extraction can be implemented to improve the accuracy; also different classification models can be implemented.

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