Assignment-5 Report

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- ## Dataset Used:

  Breast Cancer Wisconsin (Diagnostic) Data Set
  url: https://archive.ics.uci.edu/ml/machine-learning-databases/breast-cancer-wisconsin/wdbc.data

  Dataset characteristic: Multivariate
  Number of Attributes:32
  Number of Records:569
  Missing Values: None
  Associated Task: Classification
  Area: Life
  Attribute Characteristic: Real

  Detailed description of dataset: https://archive.ics.uci.edu/ml/machine-learning-databases/breast-cancer-wisconsin/wdbc.names

- ## Pre-processing:

  The data-set is directly loaded using the scikitlearn library.(using scikitlearn.datasets and using load_breast_cancer() function)

  Pseudocode:

```
  from sklearn.datasets import load_breast_cancer
  .
  .
  .
   dataset=load_breast_cancer()
```

  The dataset does not contain any missing values, however it includes unnecessary data such as ID, which is discarded in the pre-processing step. Also the data is standardized using the scikitlearn preprocessing library.

  Pseudocode:

```
   from sklearn import preprocessing
   :
   :
   X=dataset.data
Scaled_x=preprocessing.scale(X)
```

- **Pseudocode:**

```
import libraries
:
:
:
:
dataset=load_dataset
preprocessed_dataset=preprocess_scale(dataset)
:
:
List_model=[]
Model1=Load_model1(best_parameters)
List_model.append(model1)
Model2=Load_model2(best_parameters)
List_model.append(model2)
:
:
Modeln=Load_modeln(best_parameters)
List_model.append(modeln)
:
:
//cross validation, running all models one by one and displaying accuracy of each model

for name, model in models:
kfold = model_selection.KFold(n_splits=10, random_state=seed)
cv_results = model_selection.cross_val_score(model,X, Y, cv=kfold,    scoring=scoring)
results.append(cv_results)
names.append(name)
print('{:20} {:0.4f}'.format(name, cv_results.mean()*100))
final.append(cv_results.mean()*100)
```

- **Evaluation Metric Used:**

The evaluation of each model is done using two different evaluation matrices.

One of them is the accuracy of each model that we normally use. The accuracy is calculated by checking how many test instances were predicted correctly by the model. Here we are using 10-fold cross validation so the accuracy is the average accuracy of the model over 10 folds.

The other evaluation matric used is the precision matric which is calculated as follows:

Precision= True Positives / (True positives+ False positives)

The precision is averaged using the weighted average over 10 folds, the weighted average allows to take attribute imbalance into consideration.

- **Results:**

Number of instances in dataset: 569
Number of attributes in dataset: 32
How many fold cross-validation performed: 10

Classifier	Best Parameters Used	Accuracy	Precision

Decision Tree	maximum_feature=n
	min_impurity_split=0.1
		92.79 %	93.49 %

Perceptron	penalty=NONE
	n_iter=5
	warm_start=false
		90.15 %	91.06 %

Neural Net	hidden_layer_sizes=(50,45)
	activation='logistic'
	learning_rate_init=0.001
		91.56 %	92.64 %

Deep Learning	hidden_layer_sizes=(50,45,35,30,28,25,20)
	activation='identity'
	learning_rate_init=0.001
		84.55 %	80.10 %

SVM	c=10
	kernel='linear'
	tol=0.09
		94.91 %	95.42 %

Naïve Bayes	prior=default	93.68 %	94.27 %

Logistic Regression	dual=false
	max_iter=100
	tol=0.0001
		95.08 %	95.80 %

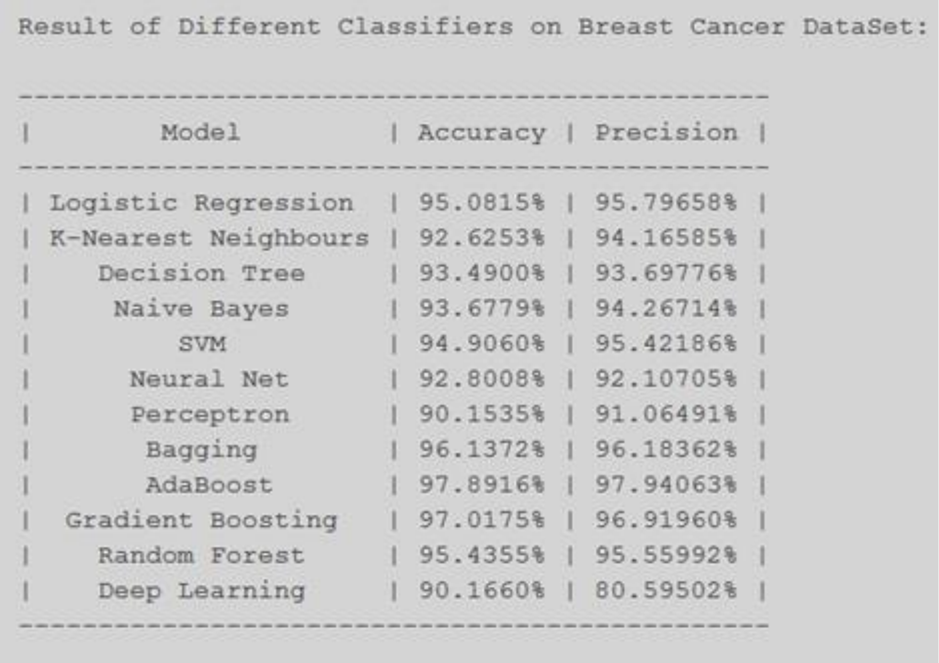
k-Nearest Neighbors	n_neighbours=9
	algorithm='ball_tree'
	weights='distance'
		92.63 %	94.20 %

Bagging	n_estimator=50
	bootstrap=true
	bootstrap_features=false
		95.96 %	96.73 %

Random Forests	n_estimator=30
	bootstrap=True
	min_impurity_split=0.00001
		95.79 %	96.51 %

AdaBoost	n_estimator=200
	algorithm='SAMME'
		97.89 %	97.94 %

Gradient Boosting	n_estimator=200
	max_depth=3
	min_impurity_split=0.0000001
		96.84 %	96.92 %



```
Result of Different Classifiers on Breast Cancer DataSet:

-----------------------------------------------
|        Model          | Accuracy | Precision |
-----------------------------------------------
| Logistic Regression   | 95.0815% | 95.79658% |
| K-Nearest Neighbours  | 92.6253% | 94.16585% |
|    Decision Tree      | 93.4900% | 93.69776% |
|     Naive Bayes       | 93.6779% | 94.26714% |
|         SVM           | 94.9060% | 95.42186% |
|      Neural Net       | 92.8008% | 92.10705% |
|      Perceptron       | 90.1535% | 91.06491% |
|       Bagging         | 96.1372% | 96.18362% |
|       AdaBoost        | 97.8916% | 97.94063% |
|  Gradient Boosting    | 97.0175% | 96.91960% |
|    Random Forest      | 95.4355% | 95.55992% |
|    Deep Learning      | 90.1660% | 80.59502% |
-----------------------------------------------
```

Screenshot of output of program.

- **Analysis:**

Each model was tested on the same data separately several times to find the best parameters for each model. Individual results of each experiment are mentioned in the logfile submitted with the assignment. Also we tried to test the model on different datasets to compare the results and found out that if the data type varies the model accuracy may vary and we found that some of the model that perform bad on some data sets perform better on other data sets. So in practice you cannot say for sure that a single model is best for all datasets, different models needs to tested and the model best suited for the particular data set should be selected.

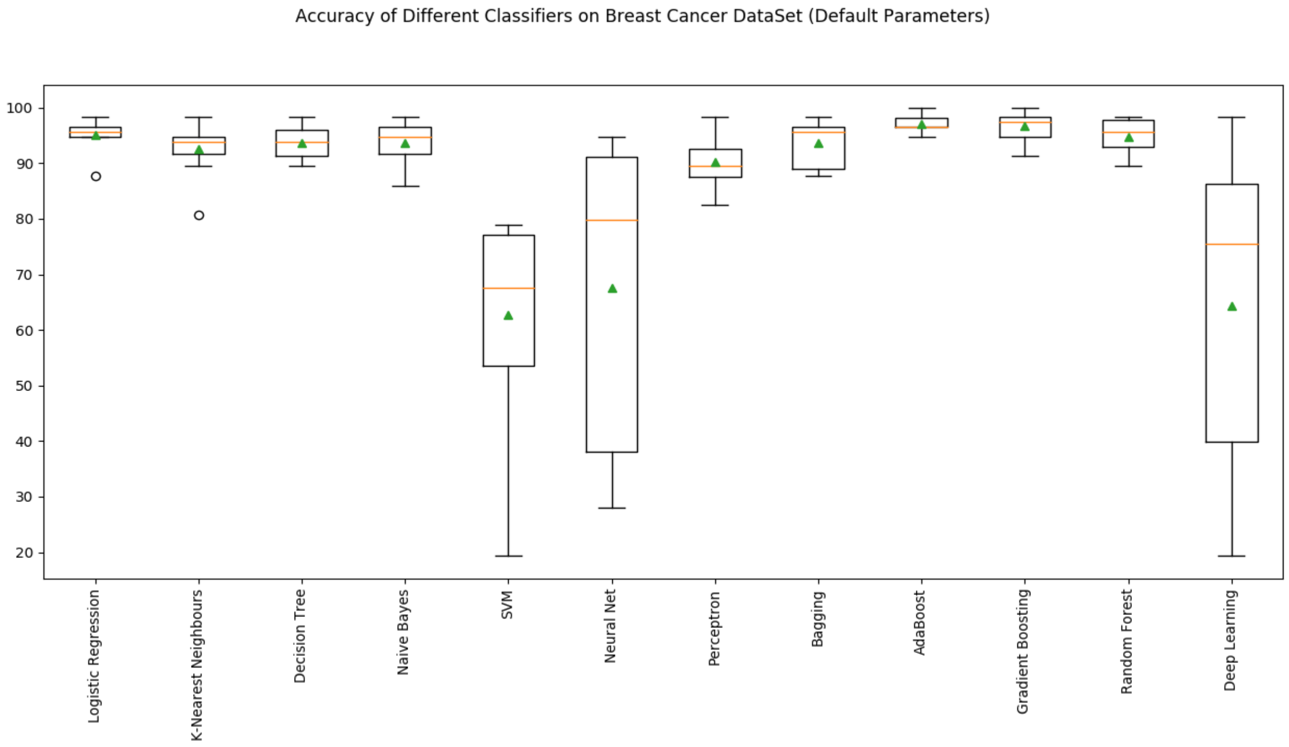
There are some models that perform better than other models in general because of their complexity and efficiency. The models that perform better in general on each type of dataset are Bagging , AdaBoost and Gradient boosting (according to our experiments). The reason for these models being better than other is obvious. These models use other models to predict the outcome several times and gradually overcomes the limitations of a single model. Also the dataset is modified by such models to avoid noise in the data.

The weakest model is the perceptron because a single perceptron tries to linearly separate which might not be possible in complex datasets. Perceptron model can still give good accuracy on some datasets if they are linearly separable and the model is tuned to the best parameters. Knn can also be considered as a week model as it just considers its neighbours to predict the outcome, but surprisingly it performs better most of the times if the model is tuned to the best suitable parameters but finding such parameters easily may not be possible for each dataset.

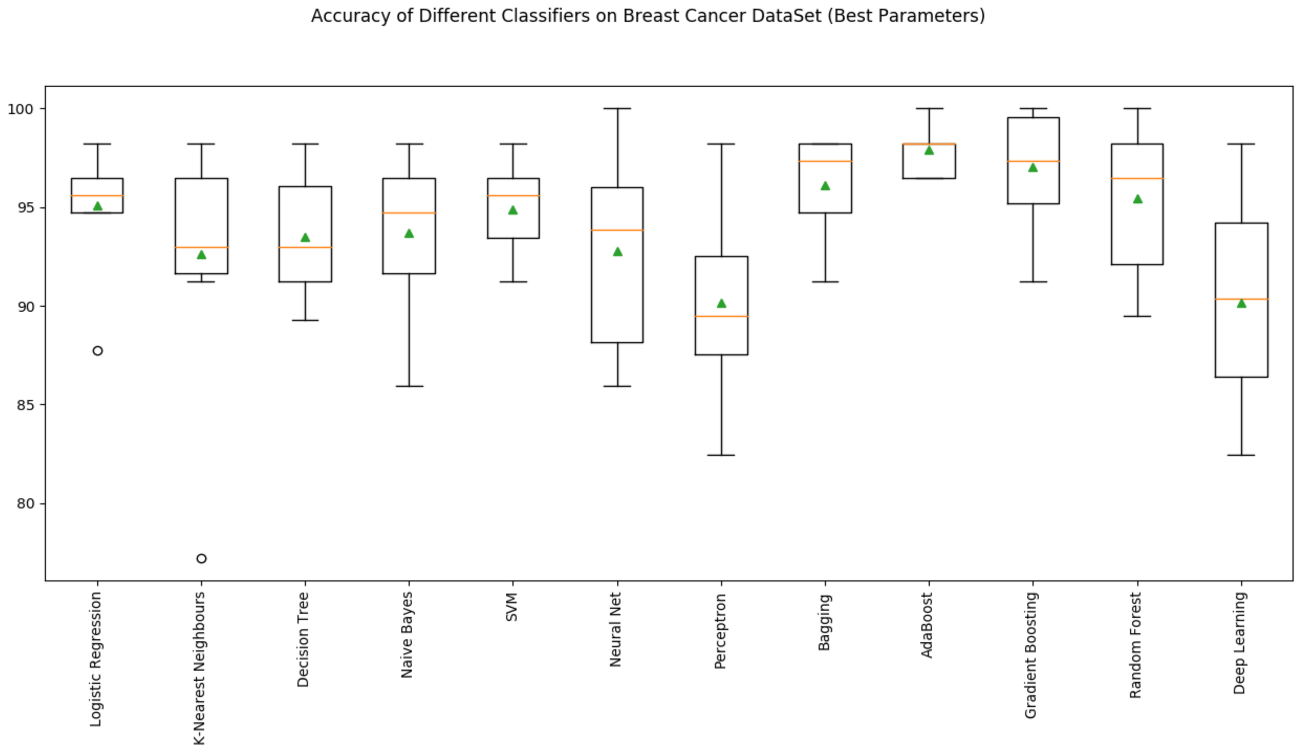
After testing each model on different parameters on same dataset we realized the importance of choosing the best parameters for each model because if we don’t use the suitable parameters with the model even the best of the models will give poor performance. Choosing appropriate parameter for the model takes time and several experiments but the result of that proves the time spent in choosing the parameter is worth.

Accuracy is used as the evaluation metric for each model but it may not be the best idea to use accuracy to compare all the models. As the accuracy only considers the correctly predicted data, it does not consider false positives and false negatives which may be required in some application of the model. We have used the precision matric to evaluate the model which is better than accuracy for comparison of models as it considers both true positives and false positives.

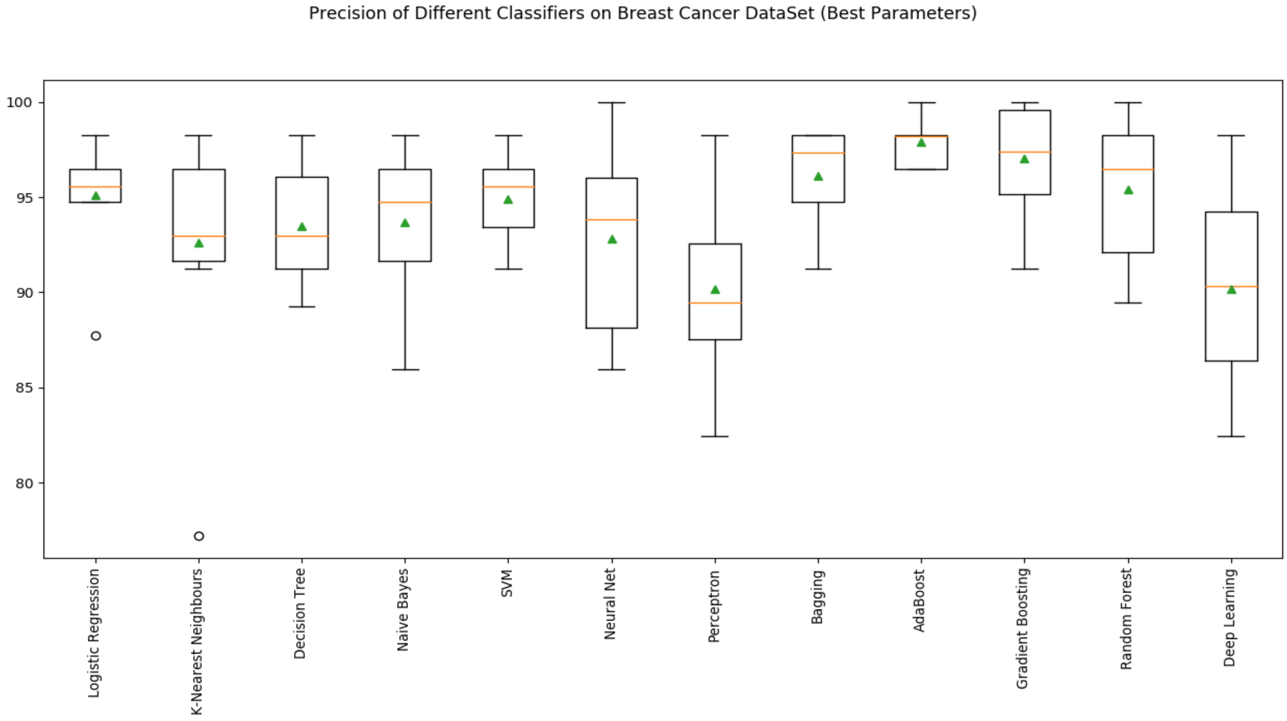
The accuracy and precision plot for one run of the complete program comparing all the models is as follows.
Accuracy plot of all models using default parameters:



Accuracy plot of all models using best parameters:



Precision plot of all models using best parameters:


Precision of Different Classifiers on Breast Cancer DataSet (Best Parameters)
Logistic Regression
K-Nearest Neighbours
Decision Tree
Naive Bayes
SVM
Neural Net
Perceptron
Bagging
AdaBoost
Gradient Boosting
Random Forest
Deep Learning