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Comparative Analysis of Machine Learning Methods for Early-Stage Diabetes Prediction

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ABSTRACT

Diabetes is a chronic disease with the potential to cause a worldwide health care crisis. According to International Diabetes Federation 382 million people are living with diabetes across the whole world. By 2035, this will be doubled as 592 million. Diabetes is a disease caused due to the increase level of blood glucose. This high blood glucose produces the symptoms of frequent urination, increased thirst, and increased hunger. Diabetes is a one of the leading causes of blindness, kidney failure, amputations, heart failure and stroke. When we eat, our body turns food into sugars, or glucose. At that point, our pancreas is supposed to release insulin. Insulin serves as a key to open our cells, to allow the glucose to enter and allow us to use the glucose for energy. But with diabetes, this system does not work. Type 1 and type 2 diabetes are the most common forms of the disease, but there are also other kinds, such as gestational diabetes, which occurs during pregnancy, as well as other forms. Machine learning is an emerging scientific field in data science dealing with the ways in which machines learn from experience. The objective of this research is to present comparative analysis of diabetes prediction using Logistic Regression and Random Forest Classifier methods. Result of Random Forest classifier outperform the Logistic Regression method in terms of accuracy 98.07 % and ROC is 0.98.

Keywords: Machine Learning, Diabetes, Logistic Regression, Random Forest Classifier, Accuracy, Confusion matrix.

I. INTRODUCTION

Diabetes is the fast-growing disease among the people even among the youngsters. In understanding diabetes and how it develops, we need to understand what happens in the body without diabetes. Sugar (glucose) comes from the foods that we eat, specifically carbohydrate foods. Carbohydrate foods provide our body with its main energy source everybody, even those people with diabetes, needs carbohydrate. Carbohydrate foods include bread, cereal, pasta, rice, fruit, dairy products and vegetables (especially starchy vegetables). When we eat these foods, the body breaks them down into glucose. The glucose moves around the body in the bloodstream. Some of the glucose is taken to our brain to help us think clearly and function. The remainder of the glucose is taken to the cells of our body for energy and also to our liver, where it is stored as energy that is used later by the body. In order for the body to use glucose for energy, insulin is required. Insulin is a hormone that is produced by the beta cells in the pancreas. Insulin works like a key to a door. Insulin attaches itself to doors on the cell, opening the door to allow glucose to move from the blood stream, through the door, and into the cell. If the pancreas is not able to produce enough insulin (insulin deficiency) or if the body cannot use the insulin it produces (insulin resistance), glucose builds up in the bloodstream (hyperglycaemia) and diabetes develops. Diabetes Mellitus means high levels of sugar (glucose) in the blood stream and in the urine.

II. LITERATURE REVIEW

Yasodha et al.[1] uses the classification on diverse types of datasets that can be accomplished to decide if a person is diabetic or not. The diabetic patient's data set is established by gathering data from hospital warehouse which contains two hundred instances with nine attributes. These instances of this dataset are referring to two groups i.e. blood tests and urine tests. In this study the implementation can be done by using WEKA to classify the data and the data is assessed by means of 10-fold cross validation approach, as it performs very well on small datasets, and the outcomes are compared. The naïve Bayes, J48, REP Tree and Random Tree are used. It was concluded that J48 works best showing an accuracy of 60.2% among others Aiswaryaet al. [2] aims to discover solutions to detect the diabetes by investigating and examining the patterns originate in the data via classification analysis by using Decision Tree and Naïve Bayes algorithms. The research hopes to propose a faster and more efficient method of identifying the disease that will help in well-timed cure of the patients. Using PIMA dataset and cross validation approach the study concluded that J48 algorithm gives an accuracy rate of 74.8% while the naïve Bayes gives an accuracy of 79.5% by using 70:30 split. Gupta et al. [3] aims to find and calculate the accuracy, sensitivity and specificity percentage of numerous classification methods and also tried to compare and analyse the results of several classification methods in WEKA, the study compares the performance of same classifiers when implemented on some other tools which includes Rapidminer and Matlabusing the same parameters (i.e. accuracy, sensitivity and specificity). They applied JRIP, Jgraft and BayesNet algorithms. The result shows that Jgraft shows highest accuracy i.e 81.3%, sensitivity is 59.7% and specificity is 81.4%. It was also concluded that WEKA works best than Matlab and Rapidminner. Lee et al. [4] focus on applying a decision tree algorithm named as CART on the diabetes dataset after applying the resample filter over the data. The author emphasis on the class imbalance problem and the need to handle this problem before applying any algorithm to achieve better accuracy rates. The class imbalance is a mostly occur in a dataset having dichotomous values, which means that the class variable have two possible outcomes and can be handled easily if observed earlier in data preprocessing stage and will help in boosting the accuracy of the predictive model.

III. METHODOLOGY

In this section we shall learn about the Logistic Regression and Random Forest Classifier methods used in machine learning to predict diabetes. A flow chart of the Logistic Regression method is depicted in figure 1 given below.

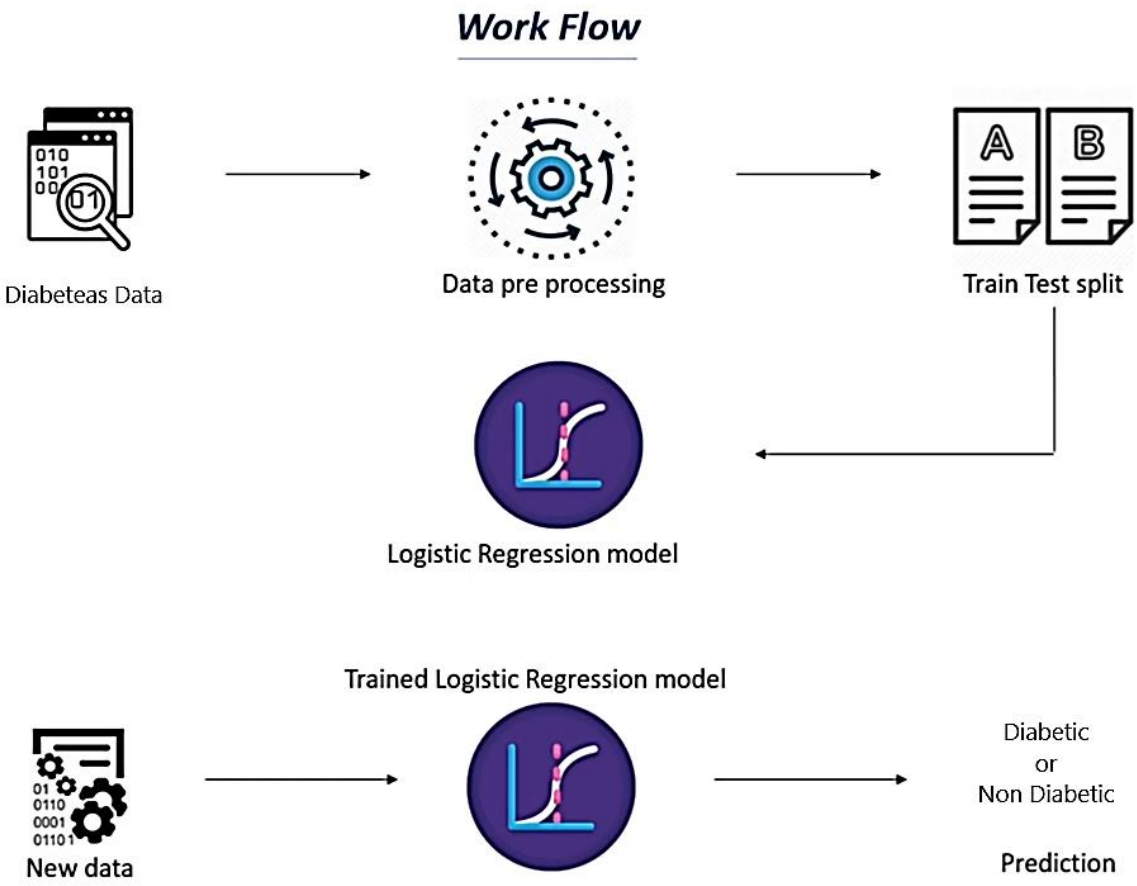


Figure-1 Flow chart of Logistic Regression method for Diabetes Perdition

The output is the accuracy metrics of the machine learning models. Then, the model can be used in prediction.

a) Dataset Description

The diabetes data set was originated from https://www.kaggle.com/johndasilva/diabetes. Diabetes dataset containing 2000 cases. The objective is to predict based on the measures to predict if the patient is diabetic or not.

b) About Data

This dataset contains the sign and symptom data of newly diabetic or would be diabetic patient.This has been collected using direct questionnaires from the patients of Sylhet Diabetes Hospital in Sylhet, Bangladesh and approved by a doctor.

c) Features of the dataset

The dataset consists of total 15 features and one target variable named class.

1. Age: Age in years ranging from (20years to 65 years)
2. Gender: Male / Female
3. Polyuria: Yes / No
4. Polydipsia: Yes/ No
5. Sudden weight loss: Yes/ No
6. Weakness: Yes/ No
7. Polyphagia: Yes/ No
8. Genital Thrush: Yes/ No
9. Visual blurring: Yes/ No
10. Itching: Yes/ No
11. Irritability: Yes/No

12. Delayed healing: Yes/ No
13. Partial Paresis: Yes/ No
14. Muscle stiffness: yes/ No
15. Alopecia: Yes/ No
16. Obesity: Yes/ No

Class: Positive / Negative

Age	Gender	Polyuria	Polydipsia	sudden weight loss	weakness	Polyphagia	Genital thrush	visual blurring	Itching	Irritability	delayed healing	partial paresis	muscle stiffness	Alopecia	Obesity	class
40	Male	No	Yes	No	Yes	No	No	No	Yes	No	Yes	No	Yes	Yes	Yes	Positive
58	Male	No	No	No	Yes	No	No	Yes	No	No	No	Yes	No	Yes	No	Positive
41	Male	Yes	No	No	Yes	Yes	No	No	Yes	No	Yes	No	Yes	Yes	No	Positive
45	Male	No	No	Yes	Yes	Yes	Yes	No	Yes	No	Yes	No	No	No	No	Positive
60	Male	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Positive

Checking Missing Values in Dataset

```
df.isna().sum()
```

```
Age                 0
Gender              0
Polyuria            0
Polydipsia          0
sudden weight loss  0
weakness            0
Polyphagia          0
Genital thrush      0
visual blurring     0
Itching             0
Irritability        0
delayed healing     0
partial paresis     0
muscle stiffness    0
Alopecia            0
Obesity             0
class               0
dtype: int64
```

Get the information about dataset

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 520 entries, 0 to 519
Data columns (total 17 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   Age                 520 non-null    int64
 1   Gender              520 non-null    object
 2   Polyuria            520 non-null    object
 3   Polydipsia          520 non-null    object
 4   sudden weight loss  520 non-null    object
 5   weakness            520 non-null    object
 6   Polyphagia          520 non-null    object
 7   Genital thrush      520 non-null    object
 8   visual blurring     520 non-null    object
 9   Itching             520 non-null    object
 10  Irritability        520 non-null    object
 11  delayed healing     520 non-null    object
 12  partial paresis     520 non-null    object
 13  muscle stiffness    520 non-null    object
 14  Alopecia            520 non-null    object
 15  Obesity             520 non-null    object
 16  class               520 non-null    object
dtypes: int64(1), object(16)
memory usage: 69.2+ KB
```

Distribution of Target Variables of Dataset

```
import seaborn as sns

sns.countplot(df['class'],data=df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x2c56d49fc10>
```

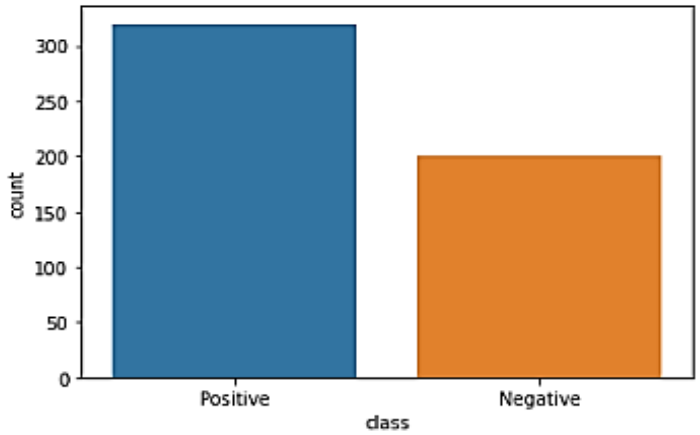


Figure 2: Distribution of target variable of diabetes dataset

Feature Selection - Top 10 Features

```
X.columns
```

```
Index(['Age', 'Gender', 'Polyuria', 'Polydipsia', 'sudden weight loss',
       'weakness', 'Polyphagia', 'Genital thrush', 'visual blurring',
       'Itching', 'Irritability', 'delayed healing', 'partial paresis',
       'muscle stiffness', 'Alopecia', 'Obesity'],
      dtype='object')
```

```
X.head()
```

	Age	Gender	Polyuria	Polydipsia	sudden weight loss	weakness	Polyphagia	Genital thrush	visual blurring	Itching	Irritability	delayed healing	partial paresis	muscle stiffness	Alopecia	Obesity
0	40	1	0	1	0	1	0	0	0	1	0	1	0	1	1	1
1	58	1	0	0	0	1	0	0	1	0	0	0	1	0	1	0
2	41	1	1	0	0	1	1	0	0	1	0	1	0	1	1	0
3	45	1	0	0	1	1	1	1	0	1	0	1	0	0	0	0
4	60	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1

d) Logistic Regression:

Logistic regression is a statistical method that is used for building machine learning models where the dependent variable is dichotomous: i.e. binary. Logistic regression is used to describe data and the relationship between one dependent variable and one or more independent variables. The independent variables can be nominal, ordinal, or of interval type. The name “logistic regression” is derived from the concept of the logistic function that it uses. The logistic function is also known as the sigmoid function. The value of this logistic function lies between zero and one.

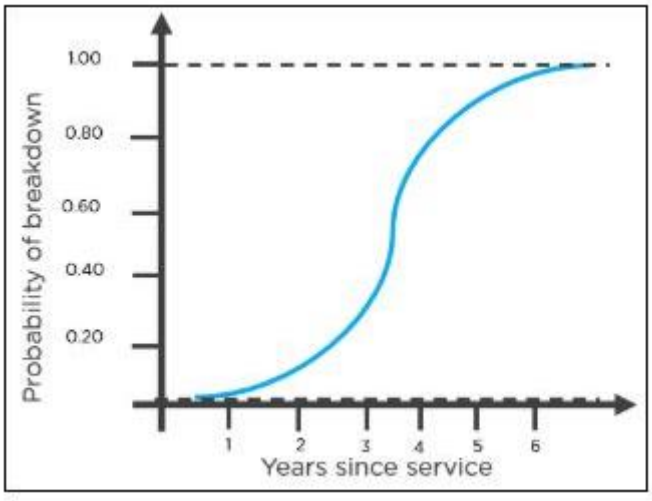


Figure 3: Sigmoid Function or Logistic Function

e) Random Forest:

A Random Forest Algorithm is a supervised machine learning algorithm which is extremely popular and is used for Classification and Regression problems in Machine Learning. We know that a forest comprises numerous trees, and the more trees more it will be robust. Similarly, the greater the number of trees in a Random Forest Algorithm, the higher its accuracy and problem-solving ability. Random Forest is a classifier that contains several decision trees on

various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset. It is based on the concept of ensemble learning which is a process of combining multiple classifiers to solve a complex problem and improve the performance of the model.

f) Working of Random Forest Algorithm

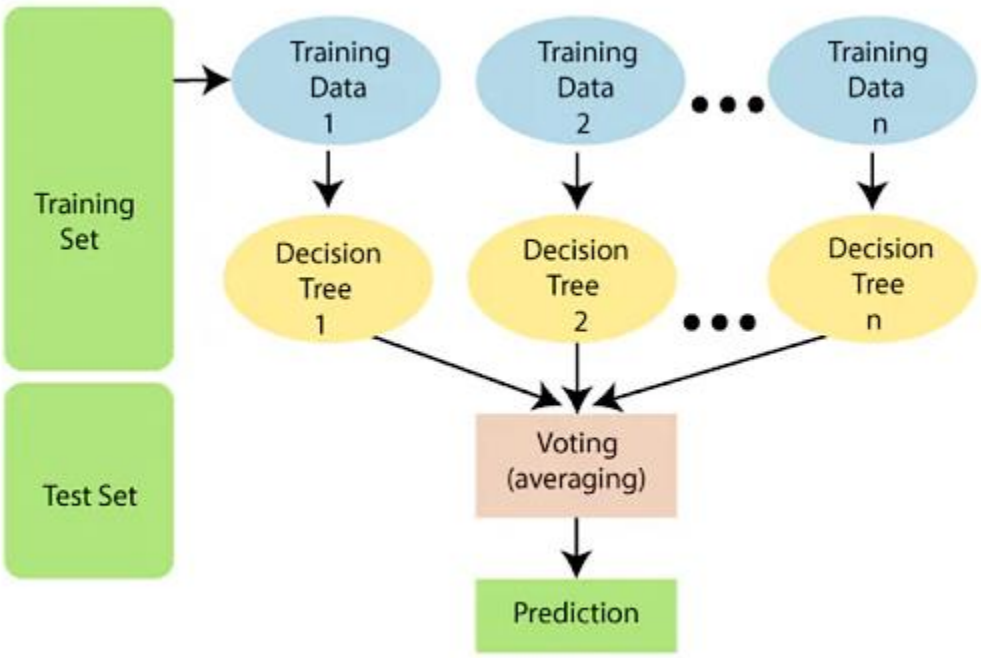


Figure 4: Working of Random Forest Algorithm

The following steps explain the working Random Forest Algorithm:

Step 1: Select random samples from a given data or training set.

Step 2: This algorithm will construct a decision tree for every training data.

Step 3: Voting will take place by averaging the decision tree.

Step 4: Finally, select the most voted prediction result as the final prediction result.

IV. RESULT & DISCUSSION

Data Correlation is a way to understand the relationship between multiple variables and attributes in your dataset. Using Correlation, you can get some insights such as: One or multiple attributes depend on another attribute or a cause for another attribute

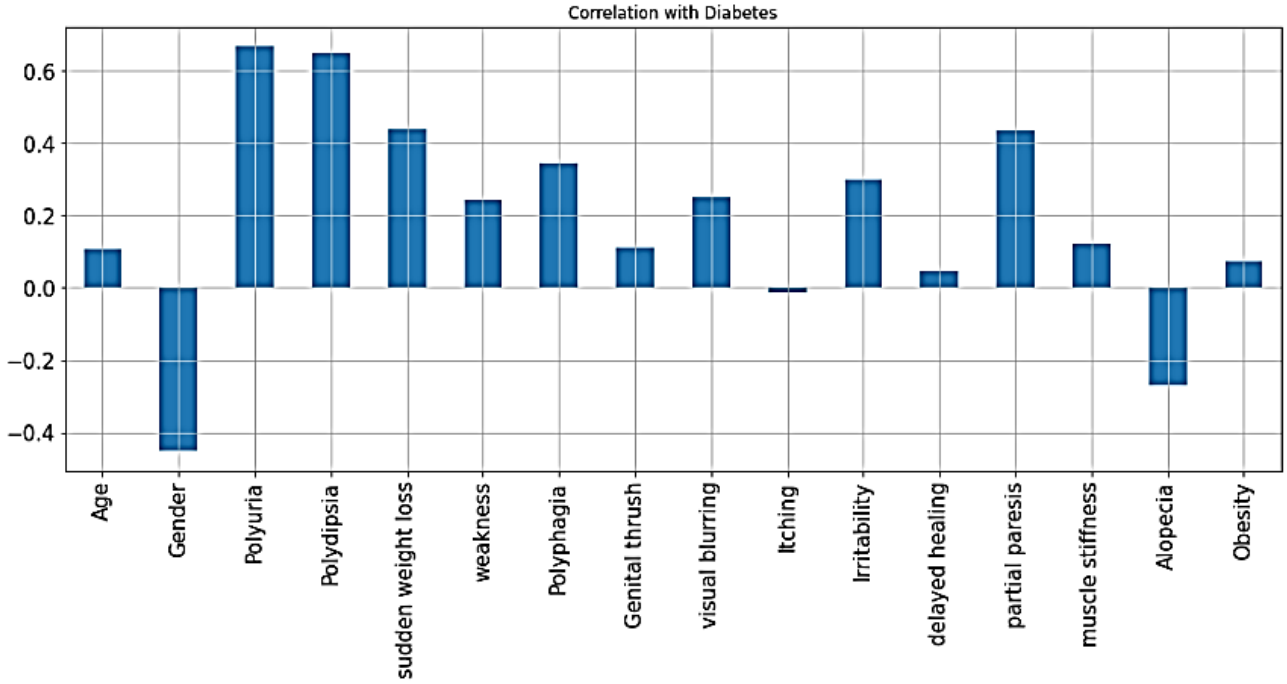


Figure 5: Correlation with Diabetes Dataset

Confusion Matrix:

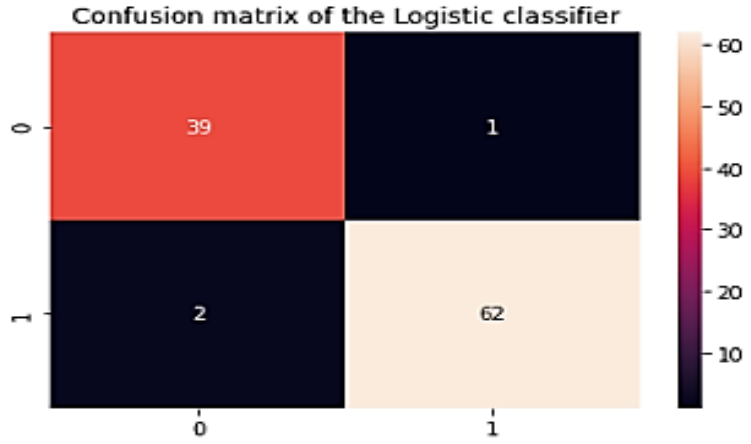
A Confusion matrix is an N x N matrix used for evaluating the performance of a classification model, where N is the number of target classes. The matrix compares the actual target values with those predicted by the machine learning model. A Confusion matrix is an *N x N matrix* used for evaluating the performance of a classification model, where N is the number of *target classes*. The matrix compares the actual target values with those predicted by the machine learning model. A good model is one which has high TP and TN rates, while low FP and FN rates.

		Predicted	
		Negative (N) -	Positive (P) +
Actual	Negative -	True Negative (TN)	False Positive (FP) Type I Error
	Positive +	False Negative (FN) Type II Error	True Positive (TP)

Figure 6: Confusion Matrix

If you have an imbalanced dataset to work with, it's always better to use confusion matrix as your evaluation criteria for your machine learning model. A confusion matrix is a tabular summary of the number of correct and

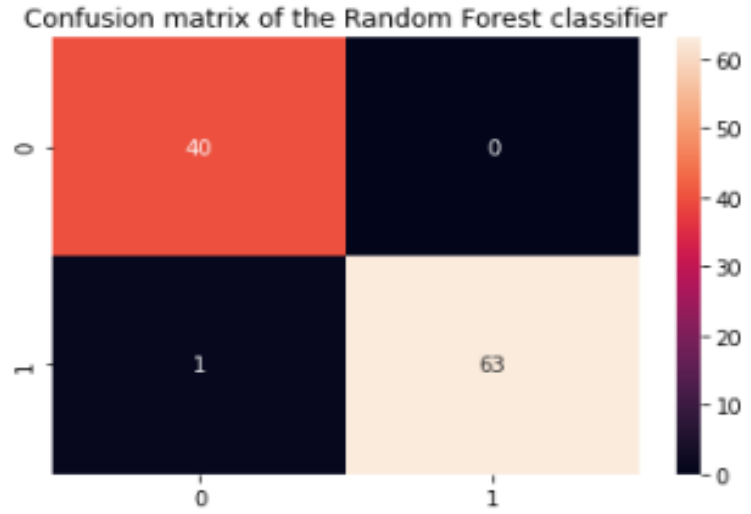
incorrect predictions made by a classifier. It is used to measure the performance of a classification model. It can be used to evaluate the performance of a classification model through the calculation of performance metrics like accuracy, precision, recall, and F1-score. Here, in this research confusion matrix of Random Forest method is 1 while in case of Logistic regression method it is 0.96.




```
TP = cm_logi[1,1] # true positive
TN = cm_logi[0,0] # true negatives
FP = cm_logi[0,1] # false positives
FN = cm_logi[1,0] # false negatives
# Let us calculate specificity
TN / float(TN+FP)
```

```
0.975
```

Figure 7: Confusion matrix of Logistic Regression Method




```
TP = cm_rf[1,1] # true positive
TN = cm_rf[0,0] # true negatives
FP = cm_rf[0,1] # false positives
FN = cm_rf[1,0] # false negatives
# Let us calculate specificity
TN / float(TN+FP)
```

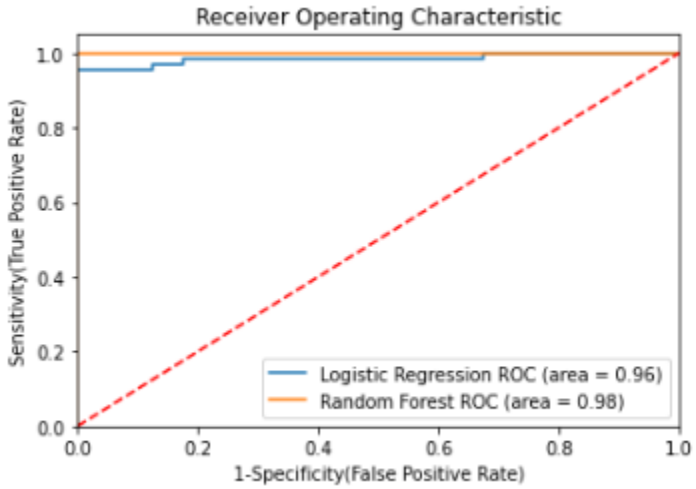
```
1.0
```

Figure 8: Confusion Matrix of Random Forest Method

	Model	Accuracy	Cross Val Accuracy	Precision	Recall	F1 Score	ROC
0	Logistic Regression	0.971154	0.918118	0.984127	0.968750	0.976378	0.971875
1	Random Forest (Untuned)	0.990385	0.978223	1.000000	0.984375	0.992126	0.992188
2	Logistic Regression-Post FS	0.961538	0.918118	0.983871	0.953125	0.968254	0.964063
3	Random Forest- Post FS	0.980769	0.963879	1.000000	0.968750	0.984127	0.984375

ROC curve:

Receiver operating Characteristic (ROC) is a graph showing the performance of a classification model at all classification thresholds. This curve plots two parameters: True Positive Rate. False Positive Rate. It has been observed that ROC value of Random Forest Classifier method is more closer to 1 as compare to Logistic Regression method. Hence, Random Forest method outperform the Logistic Regression method. The ROC curve is depicted in figure 9 given below.



V. CONCLUSION AND FUTURE WORK

One of the important real-world medical problems is the detection of diabetes at its early stage. In this study, systematic efforts are made in designing a system which results in the prediction of diabetes. During this work, five machine learning classification algorithms are studied and evaluated on various measures. Experimental results determine the adequacy of the designed system with an achieved accuracy of 98% using random Forest Classifier algorithm. In future, the designed system with the used machine learning classification algorithms can be used to predict or diagnose other diseases. The work can be extended and improved for the automation of diabetes analysis including some other machine learning algorithms.

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