# Predicting Diabetes Mellitus using Data Mining Techniques

*Comparative analysis of Data Mining Classification Algorithms*

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**Abstract— Diabetes is a chronic disease caused due to the expanded level of sugar addiction in the blood. Various automated information systems were outlined utilizing various classifiers for anticipate and diagnose the diabetes. Data mining approach helps to diagnose patient's diseases. Diabetes Mellitus is a chronic disease to affect various organs of the human body. Early prediction can save human life and can take control over the diseases. Selecting legitimate classifiers clearly expands the correctness and adeptness of the system. Due to its continuously increasing rate, more and more families are unfair by diabetes mellitus. Most diabetics know little about their risk factor they face prior to diagnosis. This paper explores the early prediction of diabetes using data mining techniques. The dataset has taken 768 instances from PIMA Indian Diabetes Dataset to determine the accuracy of the data mining techniques in prediction. Then we developed five predictive models using 9 input variables and one output variable from the Dataset information; we evaluated the five models in terms of their accuracy, precision, sensitivity, specificity and F1 Score measures. The purpose of this study is to compare the performance analysis of Naïve Bayes, Logistic Regression, Artificial neural networks (ANNs), C5.0 Decision Tree and Support Vector Machine (SVM) models for predicting diabetes using common risk factors. The decision tree model (C5.0) had given the best classification accuracy, followed by the logistic regression model, Naïve Bayes, ANN and the SVM gave the lowest accuracy**

**IndexTerms—Data mining, Prediction, Naïve Bayes, Logistic Regression, C5.0 Decision Tree, Artificial Neural Networks (ANN) and Support Vector Machine (SVM).**
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## I. INTRODUCTION

Diabetes is a dangerous disease with the potential to cause a worldwide Health Care crisis. According to International Diabetes confederation 382 million people are living with diabetes world wide. By 2035, this will be doubled as 592 million. Early prediction of diabetes is quite challenging task for medical practitioners due to complex interdependence on various factors. Diabetes affects human organs such as kidney, eye, heart, nerves, foot etc. Data mining is a process to extract useful information from large database. It is a multidisciplinary field of computer science which involves computational process, machine learning, statistical techniques, classification, clustering and discovering patterns.

### Data Mining

*Data Mining* is the process of discovering interesting knowledge, such as patterns, associations, changes, anomalies and significant structures, from large amounts of data stored in databases, data warehouses, or other information repositories. Due to the wide availability of huge amounts of data in electronic forms, and the imminent need for turning such data into useful information and knowledge for broad applications including market analysis, business management, and decision support, data mining has attracted a great deal of attention in information industry in recent years.

### Diabetes

Diabetes Mellitus (DM) is commonly referred as Diabetes; it is the condition in which the body does not properly process food for use as energy. The pancreas, an organ make a hormone called insulin to help glucose get into the cell of our bodies.

### Types of Diabetes

Type 1 Diabetes is called insulin-dependent diabetes mellitus (IDDM) or juvenile-onset diabetes.Type1 mostly occurs in young people who are below 30 years. In Type 1 Diabetes, the beta cell of the pancreas, which are in charge for insulin production, are destroyed due to autoimmune system.

Type 2 Diabetes is called non-insulin-dependent diabetes mellitus (NIDDM) or adult-onset diabetes. In the type 2 diabetes, the pancreas usually produces some insulin the amount produced is not enough for the body's needs, or the body's cells are resistant to it.

Gestational Diabetes is the third major form and occur when pregnant women without a previous account of diabetes develop a high blood glucose level. The majority of gestational diabetes patients can control their diabetes with exercise and diet. Between 10% to 20% of them will need to take some kind of blood-glucose-controlling medications. In few cases this gestational diabetes may lead to type 2 diabetes in future. It affects on 4% of all pregnant women.

### Application of Data mining Techniques in Diabetes

Medical data can be trained using data mining techniques to predict the diabetes. For this, dataset has to be preprocessed to remove noisy and fill the missing values. Pima Indian Diabetes Dataset is taken to evaluate data mining Classification. The dataset comprises 9 attributes and 768 instances.

## II. *LITERATURE REVIEW*

Design of prediction models for diabetes diagnosis has been an active research area for the past decade. Most of the models found in literature are based on Classification Algorithms and artificial neural Networks (ANNs). Some of the research papers that reviewed for this research are given below:

AiswaryaIyer, et al. [1] have employed Decision tree (J48), Naïve Bayes algorithms for predicting diabetes. They used Pima Indian Diabetes dataset; it was implemented using WEKA tool. They found Naive Bayes algorithm gave 79.56% accuracy than another for predicting diabetes.

V.AnujaKumari, R.Chitra, [12] used SVM with Radial Basis Function Kernal for classification of diabetes disease. They used MATLAB, R2010a for implementation. They found the accuracy rate as 78%.

N. Sarma, et al. [2] used Bayesian net classifier and decision tree for Predicting Diabetes Type 2. They used PIMA indian diabetic dataset.They used WEKA tool for their implementation in that they found bayes net classifier gives the accuracy level of 71-74% depending upon the number of cross validation applied on the dataset when performing the test.and decision tree gives the accuracy level of 78-80% Which is the best accuracy without implementing any neural network structure.

P.Padmaja et al. [3] used clustering concepts for character evaluation of diabetes. They evaluated 5 different clusters by using 4 algorithms, namely 1) K-means, 2) Partitioning Around Medoids(PAM), 3) Minimum spanning tree (MST), 4) Nearest Neighbours used to identify good quality clusters. The result they found was, PAM provides cluster of good quality.

G.Parthiban, S.K.Srivatsa [4] used Naïve Bayes, SVM Techniques for Diagnosing Heart Disease for Diabetic Patients. They used WEKA tool and got the result as 94.6% of accuracy for SVM.

Dr. M. Renuka Devi andJ. Maria Shyla[8] explored various Data mining techniques such as Naïve Bayes, MLP, Bayesian Network, C4.5 , ANN, Modified J48, etc…They used MATLAB and WEKA tool. In that paper, Modified J48 classifier gave 99.87% of highest accuracy.

RupaBagdi et al. [5] compared ID3 and C4.5 decision tree algorithm results. Finally they found C4.5 was more precise than ID3.

Sadri sa'di et al.[6] used Naive Bayes, RBF Network and J48 datamining algorithms for diagnosing type II diabetes. They used WEKA tool. Finally they found Naive Bayes, having the accuracy rate of 76.96% than other algorithms.

Sankaranarayanan.S et al. [7] intended to discover the hidden knowledge from a particular dataset to improve the quality of health care for diabetic patients.

Satheeskumar.B, Gayathri.P, [9] used Data mining Classification Algorithms such as CART, J48, NBTree for Analysis of Adult - Onset Diabetes. They used WEKA tool for implementing these algorithms. They found the accuracy rate as 80% for J48 algorithm when compared to other algorithms.

Tahani Daghistani and RiyadAlshammari, [10] used MNGHA, saudhi Arabia dataset to predict diabetic patients using 18 risk factors. They found RandomForest achieved the best performance when compared to other data mining classifiers.

V. Kumar and L. Velide,[11] used Data mining Approach for Prediction and Treatment Of diabetes Disease. The techniques they used as Naïve Bayes, JRip, J48 (4.5), DT, NN .They used WEKA tool for implementation. They got 68.5% of accuracy level for J48 algorithm.

Ananthapadmanaban et al., [13] developed the SVM and Naïve Bayes classification algorithms for speculating diabetic retinopathy and found out that the Naive Bayes algorithm has got the accuracy rate of 84%.

Ferreira et al., [14] used different classification algorithms like SimpleCart, J48, Simple Logistics, SMO, NaiveBayes and BayesNet for diagnosing neonatal jaundice in type1 diabetes. Among all algorithms, it was found that Simple Logistics as the best algorithm.

The paper [15] approached the aim of diagnoses by using ANNs and demonstrated the need for preprocessing and replacing missing values in the dataset being considered. Through the Modified training set, a better accuracy was achieved with lesser time required for training the set

Mukesh kumari and Dr. Rajan Vohra [16] worked on the concept of data mining is to extract knowledge from information stored in dataset and generate clear and understandable description of patterns. The techniques are attributes selection, data normalization and then classifier is applied on data set to construct Bayesian model. Bayesian network classifier was proposed for the prediction of person whether diabetic or not.

Srideivanai Nagarajan and R.M. Chandrasekaran[17] proposed a method for improvement of iagnosis of gestational diabetes with data mining techniques. Also they Analyse the performance of ID3, Naïve Bayes, C4.5, and Random tree i.e. the algorithm for supervised Learning. They used the data set of Pregnant Womens. The results they found that Random tree served to be the best one with higher accuracy and least error rate.

K.Rajesh and V.Sangeetha[20] proposed that data mining relationship for efficient classification they applied data mining techniques to classify diabetes clinical data and predict the patient being affected with diabetes or not. They applied C4.5 Algorithm gave classification rate of 91%.

Dr. B .L. Shivkumar and S Thiyagarajan c et al (2016), In this work [19], an effective machine learning algorithm is proposed for the classification of type dm patients. This machine learning algorithm used for classification will find the optimal hyper-plane which divides the various classes.

Nahla H. Barakat (2010), In this paper [20] support vector machines (SVMs) are recommended for the diagnosis of diabetes. In this, they used a description module, which is known as "black box" model of an SVM which we used for diagnostic (classification) decision. Results retrieved on diabetes dataset with the use "black box" proves that it is an emerging tool that is

delivered by intelligible SVM's for the prediction of diabetes, with prediction accuracy of 94%, sensitivity of 93%, and specificity of 94%.

**III.** *METHODOLOGY*

**NAÏVE BAYES**

The Naïve Bayes Algorithm is a probabilistic algorithm that is sequential in nature, following steps of execution, classification, estimation and prediction. For finding relations between the diseases, symptoms and medications, there are various data mining existing solution, but these algorithms have their own limitations; numerous iterations, binning of the continuous arguments, high computational time, etc. Naïve Bayes overcomes various limitations including omission of complex iterative estimations of the parameter and can be applied on a large dataset in real time. The Naïve Bayes formula shown in Fig 1

$$P(c|x) = \frac{P(x|c) \times P(c)}{P(x)}$$

**Fig 1. Naïve Bayes Formula**

**DECISION TREES C5.0**

Decision tree is a tree structure. It is in the form of a flowchart. It is used as a method for classification and prediction using nodes and internodes. The root and internal nodes are the test cases that are used to separate the instances with different features. Leaf nodes denote the class variable.

**C5.0 Algorithm**

```
C5.0 decision tree syntax
using the C5.0() function in the C50 package
Building the classifiers
m <- C5.0(train, class, trials = 1, costs = NULL)
  • train is a data frame containing training data
  • class is a factor vector with the class for each row in the training data
  • trials is an optional number to control the number of boosting iterations
    (set to 1 by default)
  • costs is an optional matrix specifying costs associated with various types
    of errors
The function will return a C5.0 model object that can be used to make predictions.
Making predictions
p <- predict(m, test, type = "class")
  • m is a model trained by the C5.0() function
  • test is a data frame containing test data with the same features as the training
    data used to build the classifier
  • type is either "class" or "prob" and specifies whether the predictions
    should be the most probable class value or the raw predicted probabilities
The function will return a vector of predicted class values or raw predicted probabilities
depending upon the value of the type parameter.
Example:
credit_model <- C5.0(credit_train, loan_default)
credit_prediction <- predict(credit_model,
    credit_test)
```

C5.0 offer a number of improvement on C4.5. They are:
 • Speed - C5.0 is much quicker than C4.5
 • Memory usage - C5.0 is added memory proficient than C4.5
 • Smaller decision trees - C5.0 gets alike results to C4.5 with significantly smaller decision trees.
 • Support for boosting - Boosting improve the trees and give them further precision.
 • Weighting - C5.0 allow you to weight diverse cases and misclassification types.
 • Winnowing - a C5.0 option repeatedly winnows the attributes to eradicate those that may be unsupportive.

**LOGISTIC REGRESSION**

The logistic function is also called as the sigmoid function and it is developed by statisticians to describe the properties of population growth in ecology, that rising quickly and maxing out to the carrying capacity of the environment. It is an S-shaped curve that can obtain any real-valued number and mapped into the values between 0 and 1.

$$1 / (1 + e^{-value})$$

where e denotes the base of the natural logarithms and the value is the actual numerical values that we want to transform. Below is the plot of the number between -5 and 5 that transformed between the range 0 and 1 using the logistic function.
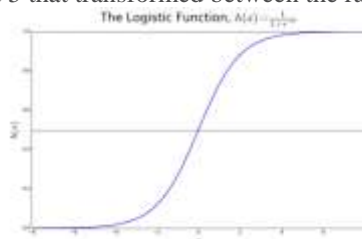


**Fig 2. The Logistic Function**

Logistic regression which uses an equation that are very much similar to linear regression. Input value (x) is combine linearly using the weights or the coefficient values (referred as the Greek letter Beta) to predict the output value (y). It's difference from linear regression is an output value is being modeled as a binary value (0 or 1) rather than the numeric values. Below is an example of logistic regression equation:

$$y = e^{(b0 + b1*x)} / (1 + e^{(b0 + b1*x)})$$

where y denotes the predicted output, b0 denotes the bias or intercept term and b1 denotes the coefficient of the input value (x). Every column in the input data has an associated b coefficient (a constant real value) that should be learned from your training data.

## ARTIFICIAL NEURAL NETWORK (ANN)

Artificial Neural network is normally organized into layers. Layers are made of lots of interconnected 'nodes' that includes an 'activation function'.
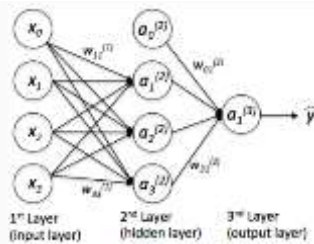


**Fig 3. Artificial Neural Network**

A neural network may include the following 3 layers:
- **Input layer** – The activities of the input unit is to represent the unrefined information that can given into the network.
- **Hidden layer** – To decide the activity of each hidden unit. The activities of the hidden units and their weights on the connection that are lie between the input and the output units. There might be one or more hidden layers in a network.
- **Output layer** – The activities of each output units are depends upon the activities of the hidden units and their weights between the hidden and output units.

## SUPPORT VECTOR MACHINE(SVM)

### (a) Introduction

Support Vector Machine is based on the concept of hyperplanes that define the decision boundaries. A hyperplane is one that separates between the set of objects that having different class members. A schematic example is given in the illustration below. In this example, the objects are belong to either class GREEN or RED. The separating line defines the boundary on the right side of which all the objects are GREEN and to the left of which all the objects are RED.
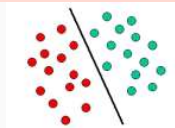


**Fig 4. Support Vector Machine**

### (b) Technical Notes

Support Vector Machine is a classifier method that perform classification task by constructing the decision planes in a multi-dimensional space that separates the case of diverse class labels. SVM supports regression and classification tasks, that can handle multiple continuous and the categorical variables. For the categorical variables, dummy variable is created with case values either 0 or 1. Thus, a categorical dependent variables consists of three levels, say (A, B, C), is represented as a set of three dummy variables:

$$A: \{1\ 0\ 0\}, B: \{0\ 1\ 0\}, C: \{0\ 0\ 1\}$$

To construct the optimal hyperplane, SVM employs an iterative training algorithm, which is used to minimize the error function. According to the form of error function, SVM models can be classified into four distinct groups:
- Classification SVM Type 1 (also known as C-SVM classification)
- Classification SVM Type 2 (also known as nu-SVM classification)
- Regression SVM Type 1 (also known as epsilon-SVM regression)
- Regression SVM Type 2 (also known as nu-SVM regression)

### (c) Classification SVM

### CLASSIFICATION SVM TYPE 1

For this type of Classification SVM Type I, training phase involves the minimization of error function:

$$\frac{1}{2} w^T w + C \sum_{i=1}^{N} \xi_i$$

subjects to the constraint:

$$y_i \left( w^T \phi(x_i) + b \right) \geq 1 - \xi_i \text{ and } \xi_i \geq 0, i = 1,..., N$$

where C denotes the capacity constant, w denotes the vector coefficients, b denotes the constant, and represents the parameter for handling non separable data (inputs). The index i labels the N training cases. Note that $y \in \pm 1$ represent the class labels and xi represent the independent variables. The kernel $\phi$ is used to transform the data from input (independent) to the feature space. It is ought to be noted that larger the C, the more error is penalize. Thus, C is ought to be chosen with care to avoid over fitting.

### CLASSIFICATION SVM TYPE 2

In contrast to Classification SVM Type 1, the Classification SVM Type 2 model minimizes the error function:

$$\frac{1}{2} w^T w - v\rho + \frac{1}{N} \sum_{i=1}^{N} \xi_i$$

subject to the constraints:

$$y_i\left(w^T\phi(x_i)+b\right)\geq \rho-\xi_i, \xi_i \geq 0, i=1,...,N \text{ and } \rho \geq 0$$

In a regression SVM, you have to estimate the functional dependence of the dependent variable y on a set of independent variables x. It assumes, like other regression problems, that the correlation between independent and dependent variables is given by a deterministic function f plus the addition of some additive noise:

## (d) Regression SVM

### REGRESSION SVM TYPE 1

For this type of Regression SVM Type1, the error function is given as

$$\frac{1}{2}w^T w + C\sum_{i=1}^{N}\xi_i + C\sum_{i=1}^{N}\xi^*_i$$

which we minimize the subject to:

$$w^T\phi(x_i)+b-y_i \leq \varepsilon + \xi_i^*$$
$$y_i - w^T\phi(x_i)-b_i \leq \varepsilon + \xi_i$$
$$\xi_i, \xi_i^* \geq 0, i=1,...,N$$

### REGRESSION SVM TYPE 2

For this type of Regression SVM Type2, the error function is given by:

$$\frac{1}{2}w^T w - C\left(v\varepsilon + \frac{1}{N}\sum_{i=1}^{N}\left(\xi_i+\xi_i^*\right)\right)$$

which we minimize the subject to:

$$\left(w^T\phi(x_i)+b\right)-y_i \leq \varepsilon + \xi_i$$
$$y_i - \left(w^T\phi(x_i)+b_i\right) \leq \varepsilon + \xi^*_i$$
$$\xi_i, \xi^*_i \geq 0, i=1,...,N, \varepsilon \geq 0$$

There are number of kernels that can be used in Support Vector Machine models. These includes linear, polynomial, radial basis function (RBF) and sigmoid models.

## (e) Kernel Functions

$$K(\mathbf{X_i},\mathbf{X_j})=\begin{cases}\mathbf{X_i}\cdot\mathbf{X_j} & \text{Linear}\\ (\gamma\mathbf{X_i}\cdot\mathbf{X_j}+C)^d & \text{Polynomial}\\ \exp(-\gamma|\mathbf{X_i}-\mathbf{X_j}|^2) & \text{RBF}\\ \tanh(\gamma\mathbf{X_i}\cdot\mathbf{X_j}+C) & \text{Sigmoid}\end{cases}$$

where $K(\mathbf{X_i},\mathbf{X_j})=\phi(\mathbf{X_i})\bullet\phi(\mathbf{X_j})$ that is, the kernel function, that represents the dot product of input data points that is mapped into the multidimensional space by transformation.

## IV Performance Evaluation

### 1. PERFORMANCE METRICS

#### a) Dataset Description and Pre-Processing

The classification type of data mining has been applied to the Pima Indians Diabetes Dataset from UCI repositories. Table 1 shows a brief description of the dataset that is being considered.

**Table 1 Dataset Description**

| Dataset | No. of Attributes | No. of instances |
|---|---|---|
| Pima Indian Diabetes Dataset | 9 | 768 |

The attributes descriptions are shown in Table 2 below.

**Table 2 Attribute Description**

| Attribute No. | Attribute | Description |
|---|---|---|
| 1 | Pregnancies | Number of times pregnant |
| 2 | Glucose | Plasma glucose concentration a 2 hours in an oral glucose tolerance test |
| 3 | BloodPressure | Diastolic blood pressure(mmHg) |
| 4 | SkinThickness | Triceps skin fold thickness(mm) |
| 5 | Insulin | 2-Hour serum insulin (mu U/ml) |
| 6 | BMI | Body Mass Index(BMI) |
| 7 | DiabetesPedigreeFunction | Diabetes Pedigree function |
| 8 | Age | Age(in years) |
| 9 | Outcome | Class variable(0 or 1) |

Pre-processing and transformation of the dataset are done using R tools.
Transformation steps include:
- Replacing missing values, and
- Normalization of values.

The descriptive statistics of the dataset is presented in Table 3. Since the parameters are normalized the range of all are in the range 0 to 1.

**Table 3 Descriptive Statistics of Transformed Dataset**

| Parameter | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|
| Glucose | 0 | 1 | 0.608 | 0.161 |
| BMI | 0 | 1 | 0.477 | 0.117 |
| DiabetesPedigreeFunction | 0 | 1 | 0.168 | 0.141 |
| Age | 0 | 1 | 0.204 | 0.196 |

**b) Evaluation of Classifiers Performance Metrics**

This paper used confusion matrix to appraise the performance of the five models for incidence of diabetes and five evaluated indices for accuracy, sensitivity, specificity, Precision and F1 Score.

- Accuracy = (TP + TN)/(TP + FP + TN + FN)
- Sensitivity = TP/(TP+FN)
- Specificity = TN/(FP+TN)
- Precision = TP/(TP+FP)
- F1 Score = (2*Precision*Recall)/(Precision+Recall)

where TP, TN, FP and FN denote true positives, true negatives, false positives and false negatives, respectively. The model with highest the sensitivity, specificity, and accuracy is the best predictive model.

**c) Time Calculation**

The execution time for each classifier algorithms are calcuted by using the following R Tool command:
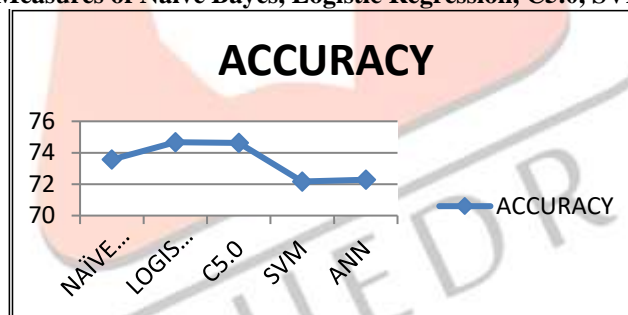
**Sys.time( )**

## 2. PERFORMANCE ANALYSIS OF THE CLASSIFIER

**a) Accuracy Measures:**

The Accuaracy measures of Data mining Classification Algorithms, i.e., Naïve Bayes, Logistic Regression, Decision Tree C5.0, SVM and ANN and their analysis report is given in the following Table 4

| ALGORITHMS | ACCURACY |
|---|---|
| NAÏVE BAYES | 73.57% |
| LOGISTIC REGRESSION | 74.67% |
| C5.0 | 74.63% |
| SVM | 72.17% |
| ANN | 72.29% |

**Table 4 Accuracy Measures of Naïve Bayes, Logistic Regression, C5.0, SVM and ANN**



**Fig 5. Analyzing the Accuracy Measures of Naïve Bayes, Logistic Regression, C5.0, SVM and ANN**

## IV. Time Analysis:

The time taken by all the five Data mining Classification Algorithms, i.e., Naïve Bayes, Logistic Regression, C5.0, SVM and ANN are calculated and it is analyzed in the following Table 5

| ALGORITHMS | TIME ANALAYSIS (in mins) |
|---|---|
| Naïve Bayes | 2.51 |
| Logistic Regression | 2.23 |
| C5.0 | 1.67 |
| SVM | 1.89 |
| ANN | 4.55 |

**Table 5 Time Taken by Naïve Bayes, Logistic Regression, C5.0, SVM and ANN**
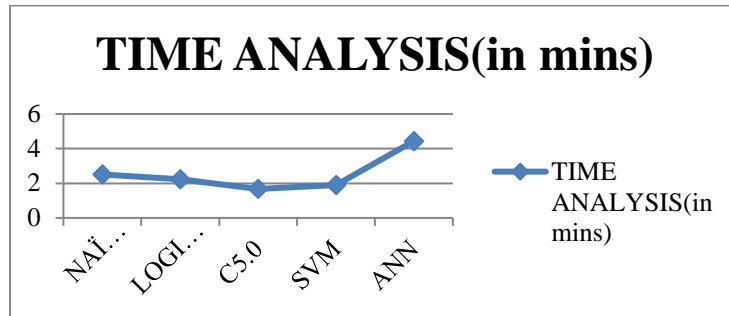
**Fig 6. Analyzing the Time taken by Naïve Bayes, Logistic Regression, C5.0, SVM and ANN**

## V. Other Metric Measures:

The other Metric Measures say Precision, Sensitivity, Specificty and F1 Score measures are also calculated and it is shown in the following Table 6

| ALGORITHMS | PRECISION | SENSITIVITY | SPECIFICITY | F1 SCORE |
|---|---|---|---|---|
| NAÏVE BAYES | 61.84% | 60.2% | 80.5% | 61.04% |
| LOGISTIC REGRESSION | 69.12% | 55.95% | 85.52% | 61.84% |
| C5.0 | 65.3% | 65.31% | 80% | 65.3% |
| SVM | 64.81% | 43.75% | 87.33% | 52.24% |
| ANN | 64.62% | 50.6% | 84.46% | 56.76% |

**Table 6 Precision, Sensitivity, Specificity and F1 measures of Naïve Bayes, Logistic Regression, C5.0, SVM and ANN**
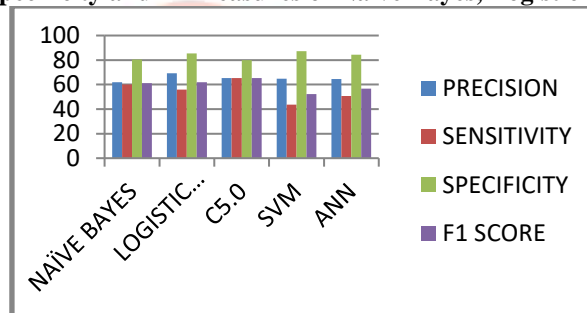


**Fig 7 Analyzing the Precision, Sensitivity, Specificity, F1 Score Measures of Naïve Bayes, Logistic Regression, C5.0, SVM and ANN**

## 4 Overall Performance Analysis

The overall performance analysis of Naïve Bayes, Logistic Regression, C5.0, SVM and ANN algorithms are shown in the following Table 7

| METRIC MEASURES | NAÏVE BAYES | LOGISTIC REGRESSION | C5.0 | ANN | SVM |
|---|---|---|---|---|---|
| ACCURACY | 73.57 | 74.67 | 74.63 | 72.29 | 72.17 |
| PRECISION | 61.84 | 69.12 | 65.3 | 64.62 | 64.81 |
| SENSITIVITY | 60.2 | 55.95 | 65.31 | 50.6 | 43.75 |
| SPECIFICITY | 80.5 | 85.52 | 80 | 84.46 | 87.33 |
| FI SCORE | 61.04 | 61.84 | 65.3 | 56.76 | 52.24 |

**Table 7. Overall Performance Analysis of Naïve Bayes, Logistic Regression, C5.0, SVM and ANN**
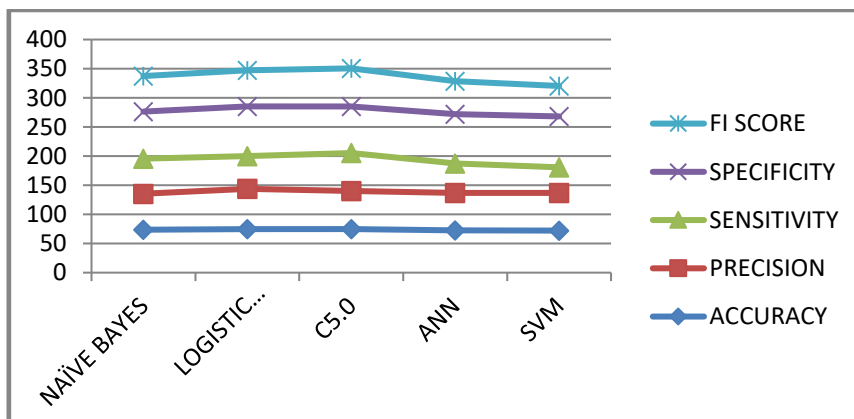


**Fig 8. Overall Performance analysis of Naïve Bayes, Logistic Regression C5.0, SVM and ANN**

*V CONCLUSION AND FUTURE ENHANCEMENT*

## 1. CONCLUSION

The automatic diagnosis of diabetes is an important real-world medical problem. Detection of diabetes in its early stages is the key for treatment. This paper shows how the Data mining classification algorithms say Naïve Bayes, Logistic Regression, C5.0, SVM and ANN are used to model actual Prediction of Diabetes Mellitus and a comparative analysis are made between them by making use of their Metric Measures say Accuracy, Precision, Sensitivity, Specificity and F1 Score.

As a results of the research work, the C5.0 and Logistic Regression are equally good based on their Accuracy measures, the Naïve Bayes algorithm has the Second highest accuracy, followed by ANN and the most lowest accuracy is predicted in the SVM algorithms.

## 2. FUTURE ENHANCEMENT

In future it is planned that the work can be extended and improves for the automation of diabetes analysis. In future the diabetes can be prevented using gene analysis from the previous history of the diabetes. Future work will focuses on collecting real time dataset and discover the new potential prognostic elements that are to be incorporated. The Fuzzy Logic can be included in future to diagnoise the diabetes types automatically.

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