A Comparative Study of Supervised Machine Learning Techniques for Diagnosing Mode of Delivery in Medical Sciences

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***Abstract*—The uses of machine learning techniques in medical diagnosis are very helpful tools now-a-days. By using machine learning algorithms and techniques, many complex medical problems can be solved easily and quickly. Without these techniques, it was a difficult task to find the causes of a problem or to suggest most appropriate solution for the problem with high accuracy. The machine learning techniques are used in almost every field of medical sciences such as heart diseases, diabetes, cancer prediction, blood transfusion, gender prediction and many more. Both supervised and unsupervised machine learning techniques are applied in the field of medical and health sciences to find the best solution for any medical illness. In this paper, the implementation of supervised machine learning techniques is performed for classifying the data of the pregnant women on the basis of mode of delivery either it will be a C-Section or a normal delivery. This analysis allows classifying the subjects into caesarean and normal delivery cases, hence providing the insight to physician to take precautionary measures to ensure the health of an expecting mother and an expected child.**

***Keywords*—Machine learning; supervised learning; bioinformatics; medical sciences**

I. Introduction

Bioinformatics is now-a-days the most important field that is associated with the concepts of machine learning. Almost every main medical problem can now be solved by implementing the machine learning techniques such as classification, regression analysis, clustering, etc. [1] [2] [3]. Both supervised and unsupervised machine learning techniques can be implemented on medical datasets, based on the nature of the data and the type of results to be inferred from the data.

There is a huge corpus of data available for applying machine learning techniques related to the medical problems. In almost every field of Bioinformatics, the techniques of machine learning are implemented and providing very helpful results for the diagnosis of the disease. The use of these techniques is very helpful for the medical technicians and doctors as well as practitioners to correctly perform the treatment of a disease. These techniques are also supportive for the future researchers to devise more ways of solving the problems related to any medical issue effectively. In short, machine learning has provided a new life span to the field of Bioinformatics for solving medical related issues.

Many datasets are also available online about the domain of maternity related cases. Many different types of judgements can be performed related to those datasets, such as gender prediction of a child, weight of new born baby, mode of delivery of the baby and many more. The correct prediction about the birth mode of a child is important, not only for the survival of the new born but also for the health of a becoming mother. So, decision about the mode of delivery of a woman should be carried out very carefully. In this research, a medical dataset consisting of the real-world values from the medical records of the pregnant women has been obtained for evaluating machine learning techniques to select the most appropriate technique for solving such type of problems.

Machine learning is a scientific discipline which focuses on how machines learn from the given data. Machine learning is a field of artificial intelligence, that provide a system of automated learning and producing the desired outcome from the given dataset based on the previous examples from the same domain.

Samuel, the father of machine learning term divided it in Supervised and Unsupervised categories [4]. In supervised learning, we have a training data, with a defined set of rules. Based on those rules, the testing data will be evaluated. The

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main goal of supervised machine learning is to predict a known output or target from a huge volume of the input data. Because of these predictions, the evaluation of the learning methods will be performed by classifying some metrics. Supervised machine learning techniques are very important for performing Classification, Inference or Regression analysis on a set of data [5] [6] [7]. A study [8] discussed that a supervised machine learning model is built by dividing a dataset into two parts: One set is used for building a classification model by assigning every attribute to one of the defined class labels. The other is for testing the classification model.

In unsupervised learning, there are no group boundaries defined and patterns are matched and recognized from the data that has no labels for identification of the data. Unsupervised learning is a type of machine learning algorithm used to draw implications from datasets consisting of input data without labelled responses. The most common unsupervised learning method is cluster analysis, which is used for exploratory data analysis to find hidden patterns or grouping in data.

The main motivation for this research is to provide aid to the pregnant women for getting their new born baby healthier and in a safe way. No doubt, the maternity related issues are very delicate to handle and solve as, it is the matter of two lives and a concern of a whole family. So, in this research, the focus is to perform some affective work for the betterment of expecting women and to help the medical officers for performing the maternity related delicate decision about the mode of delivery very carefully and correctly.

The problem to be solved in this research work is about the classification of the data of pregnant women in to Caesarean Section or Normal, identifying their mode of delivery based on the number of attributes describing different aspects of a pregnant woman. The Supervised machine learning techniques of Classification are applied on the sampled dataset for assigning a class label of either 0 or 1 to an expecting woman. This classification will be done by using the techniques of Neural Networks, Support Vector Machines (Linear) and Tree based classification (Random Forest, CTree, RPART).

The rest of the paper is organized as follows. Related previous work is reviewed in Section II. Section III describes the data used in the research and the techniques and tools adopted to perform the classification techniques. The results of the experiments in the form of accuracy metrics, ROC curves and graphs are discussed in Section IV. Section V provides conclusion and recommendations for the future work.

II. Literature Review

There is a huge volume of research work performed to determine relationship between C-Sections and inter related risk factors. Defined maternal age of above 44 has more chances of medical complications [9] e.g. hypertension and diabetes and results in higher rate of C-Section delivery. They used machine learning techniques [10] to find if high blood pressure and pulse rate, lack of education and low income, previous surgery and multivitamins are causes of C-Section delivery. Hueston defined site to site variations have chances of C-Section delivery [11]. They said that patients of age greater than or equal to 35 cannot effect in C-Section delivery but if weight is greater than 3600gm and age is also greater than 35 than there are more chances of C-Section delivery [12].

A research about C-Section delivery in 2015 reported that wealth and education effect C-Section delivery [13]. 23 to 35 per cent C-Section deliveries occur in high income people and 12 per cent C-Section deliveries of low income group. Same as higher education have higher C-Section deliveries, the women with no education have C-Section birth rate 7.5 and the metric, secondary and higher education have 21, 31 and 41 per cent, respectively. If there was a previous C-Section birth, then there are more chances of C-Section birth.

Another research described that many factors are involved in C-Section [14]. Major factors for C-Section delivery showed the relationship between section birth, wealth, education, age, ultrasonography, pregnancy completions. Private hospitals have more C-Section delivery as compare to the public. A study said that maternal age affects the C-Section delivery [15]. The authors divided the age in 3 groups. One group is less than 35, another is between 35 and 39 and one group is above 40. Authors defined that the age of 35 -39 have increasing risk of miscarriage and felt chromosomes abnormalities and age of 40 and above have risk factors of gestational diabetes, placenta Persia, placenta abrupt and C-Section delivery.

A reasonable amount of work has been performed on the coeliac disease effect on the new born [16]. They studied that if father suffered from any coeliac disease, new born have lower birth weight and shorter pregnancy duration. If mother suffer from coeliac then birth weight of new born will also be low. The factors of cigarette smoking and hypertension during pregnancy increase the risk in placental abruption [17]. Women that use less calcium level in diet, have more chances of increase blood pressure in their pregnancy [18]. Deficiency of calcium level creates more chances of preeclampsia in the women in pregnancy. They need calcium supplementation to decrease hypertension disorders. Effect of rotation of the head direction of the foetus inside the uterus has a great impact on the mode of delivery of a baby [19]. The researchers studied the effects of rotation of the foetal head on the probable outcome of the delivery mode.

The effects of medical complications that cause C-Section are very important to handle with great care. In a study [20], they discussed the scope of elective caesarean section without any medical complications. They discussed that the rate of C-Section deliveries is increasing day by day mostly due to the elective mode of delivery. A survey was conducted by interviewing the expected mothers about their own choice of the mode of birth and most of the women selected C-Section, because majority of women think that it is a safe way for the baby as compared to the vaginal birth.

The maternal age of the expecting mother also influences the mode of delivery either it will be a C-Section or a normal birth. They performed an analysis about the impact of the maternal age on the mode of delivery of an expecting woman [21]. They discussed that the women with age more than 35 years have a caesarean section of about 46.1% and that of the age between 30 to 34 years was 40.9%. They showed that only age is not the influencing factor on the mode of delivery. Besides age there are many other factors such as stress, fatigue, posture of working, economic status is also affecting the birth mode of a becoming mother.

The effect of maternal age and the foetal sex are also considered a cause of C-section in most of the expecting women. They discussed that the foetal sex and maternal age combine affect the mode of delivery of a woman [22]. They showed that the risk of operative deliveries increased with a woman of age >40 and carrying a male foetus. The risk of maternal diabetes and increased hospitalization of the women having age<40, but carrying a male foetus also become a cause of operative or caesarean section delivery.

A smart decision support system is available for performing statistical analysis for finding different results. An analysis applied machine learning techniques on smart decision support systems for prediction of the correct treatment methods for a pregnant woman [23]. A comparison between two Bayesian classifiers is performed to classify hypertensive disorder severity among the pregnant women and the results showed that the Bayesian classifier produces the best results with a precision of 0.400 as compared to AODE which has a precision of 0.275.

III. Methodology

The attributes of the dataset are listed with their types and full description in the Table I. Besides all these attributes, a class attribute is used for performing the classification of the data based on the values given to the attributes about a specific entity. Based on the values of the attributes, it is decided that a specific entity is assigned to a class with label 0 or 1. The accuracies of the applied techniques are calculated and the Kappa values for these accuracies are also observed. Based on these calculations, the best methods for solving such type of problems are suggested.

The techniques of Artificial Neural Networks (ANNs), Support Vector Machines (SVM), Random Forests (RF), Recursive Partitioning (RPART) and Conditional inference Tree (CTree) are applied on the dataset. After applying these techniques, the results are recorded and presented in the form of tables, curves and graphs.

TABLE. I. Attribute Description for the Dataset

S#	Name	Description	Type
1	Age	Age of the patient	Integer (17-40)
2	Fp	First pregnancy or not	Binary
3	Pcp	No. of pregnancies before the current pregnancy	Integer
4	Lb	No. of live births	Integer
5	Boys	No. of boys	Integer
6	Girls	No. of girls	Integer
7	Abortin	No. of abortions	Integer
8	Miscag	No. of miscarriages	Integer
9	Last_mode	Mode of last delivery	Binary
10	Inherited	Husband having any inherited disease or not	Binary
11	Menstrual	Having menstrual regular or not	Binary
12	Days_mentcal	No. of days of menstruation cycle	Integer
13	Last_time	Last time of menstruation	Integer
14	Bleeding	Having bleeding or not	Binary
15	Fatigue	Feeling fatigue during pregnancy or not	Binary
16	Diabetic	Having any diabetes disease or not	Binary
17	Breathing	Having breathing issue or not	Binary
18	Headache	Having headache or not	Binary
19	Fast_bet	Having fast heart beat or not	Binary
20	Surgery	Having any surgery before or not	Binary
21	Hemoglobin	Hemoglobin level	Integer
22	BMAX	Blood pressure maximum	Integer
23	BMIN	Blood pressure minimum	Integer
24	BPORNOT	Having BP issue or not	Binary
25	Medcin	Taking any medication or not	Binary
26	Headic	Any sort of tension or not	Binary
27	Hyperten	Having any hypertension disorder or not	Binary
28	FA	Taking Folic Acid tablets or not	Binary
29	Iron	Taking iron supplements or not	Binary

IV. Performance Evaluation

In this section, we discuss the experimental setup and tools used for evaluation. Further, the results are presented and discussed in detail.

A. Experimental Setup

The evaluation of algorithms is carried out by using RStudio tool, which is the most user-friendly tool available for performing machine learning tasks on any given dataset. Before processing the data using RStudio, the dataset was converted into CSV format. The evaluation results of ANN, SVM, RF, RPART and CTREE algorithms are gained and a comparison between the results is performed to judge the most appropriate technique for performing such type of classification jobs.

Further, the evaluation of the algorithms is carried out by using the cross-validation method, which is the most frequently used method for performing the validation on a collected set of data for statistical analysis. The 10-fold cross validation is the most important type of validation that is mostly used in evaluation of different machine learning techniques. In this method, the whole dataset is divided into 10 equal parts/folds. The evaluation is performed by selecting one of the folds as a test set and the remaining 9 folds as the training data. The same procedure is repeated each time for every fold of the data set. In this way, 10 iterations will be performed on the supplied data for validation of the results of the accuracies required by the given machine learning techniques.

The dataset is divided into two halves of 75% and 25% size. One is used as training dataset and the other is used for testing the results based on the training dataset values. After doing this process, the most accurate results about the analysis of the data are obtained.

B. Implementation Tools

RStudio is a free open source Integrated Development Environment tool available online for performing machine learning tasks with the help of statistical analysis. It provides an interactive environment that provides the facility of coding, debugging, plotting different types of graphs and viewing the history of the previous code run. It contains a set of built in libraries and functions for performing different tasks. It provides an interactive environment to the users for making the implementation of different machine learning techniques easy and efficient. We can perform classification and clustering of data using RStudio. The ROC curves can be created using RStudio for viewing the result of the applied techniques graphically for comparison or analysis. RStudio provides an environment to the user for performing the data manipulation easily and efficiently. All the coding is done in the R language by using different packages and libraries. There are many built-in libraries and packages available with the RStudio application software. R programming Language is the base of the RStudio application. Any computer running RStudio must have installed R language prior to RStudio.

C. Results

The accuracies and Kappa statistic values for the data are calculated and the results are shown in the tabular form for interpretation. Next the Receiver Operating Curves are created for each technique to check the overall accuracies of the mentioned techniques. After that graphs are plotted for interpretation of accuracies and Kappa values of all the folds in 10-fold cross validation. Table II shows the accuracy values of RF, SVM, RPART, CTREE and NNET. Results show that the accuracy of RF Algorithm is highest among all the five mentioned techniques followed by NNET, RPART, CTREE and SVM in the descending order. RF has highest accuracy value of 0.9972. The accuracy of NNET is 0.9863, RPART is 0.9838, CTREE is 0.9835, and SVM is 0.9784.

Table III shows the Kappa statistics values for all the five classifiers and provides an insight about the performance of the classification algorithms. Results show the Kappa statistics values for RF, SVM, RPART, CTTREE and NNET. These values depict that Random Forest algorithm shows the highest Kappa value of 0.9941 for the given data. The Neural Net has second highest value 0.9710, after that the value of Recursive Partitioning is 0.9666, then CTREE has 0.9657 and at last SVM has the value 0.9551. These statistics show that RF shows highest associativity among the values of different attributes of the given dataset.

TABLE. II. Accuracy Values of Classifiers

Classifier	**Min.**	**1stQuadrant**	**Median**	**Mean**	**3rd Quadrant**	**Max.**	**NA's**
RF	0.9722	1.0000	1.0000	0.9972	1	1	0
SVM	0.8947	0.9722	0.9861	0.9784	1	1	0
RPART	0.9211	0.9722	1.0000	0.9838	1	1	0
CTREE	0.9444	0.9722	0.9868	0.9835	1	1	0
NNET	0.9722	0.9724	0.9865	0.9863	1	1	0

TABLE. III. Kappa Statistics Values of Classifiers

Classifier	**Min.**	**1st Quadrant**	**Median**	**Mean**	**3rd Quadrant**	**Max**	**NA's**
RF	0.9408	1.0000	1.0000	0.9941	1	1	0
SVM	0.7847	0.9412	0.9712	0.9551	1	1	0
RPART	0.8403	0.9423	1.0000	0.9666	1	1	0
CTREE	0.8861	0.9423	0.9721	0.9657	1	1	0
NNET	0.9417	0.9423	0.9712	0.9710	1	1	0

The results of training and validation accuracies are combined for performing a comparative analysis of training and validation results of the data. Fig. 1 shows the comparison of training and validation accuracies of the classification techniques. CTREE has highest set of values for both training and validation results of the data and RPART has highest accuracy values. NNET with third highest accuracy, RF has values 96.15616 and 100 for training and validation respectively. SVM shows lowest values among all. This plot shows that all the applied techniques have better accuracy values for the validation data set as compared to the training part of the data. RPART and CTREE have highest points in this plot.

Next the ROC curves for all the five classifiers are obtained by using the RStudio. Fig. 2 shows the overall accuracies of NNET, SVM, RF, RPART and CTREE as a whole. Results show the classification of the given dataset into normal and C-Section values according to given class labels assigned. The area under the curve shows the sensitivity over specificity for NNET is 1.000, SVM is 0.993, RF is 1.000, RPART is 1.000 and CTREE is 1.000. Results depict that NNET, RPART, CTREE and RF have maximum sensitivity to specificity ratio.

Fig. 3 depicts the training and testing accuracies of all the techniques. Results show that in the testing phase, Tree-based techniques are providing better accuracy values as compared to other techniques on the given dataset.

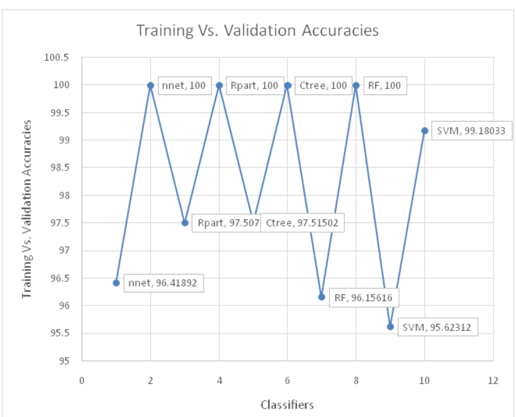

Fig. 1. Training vs Validation Accuracies of Classifiers.

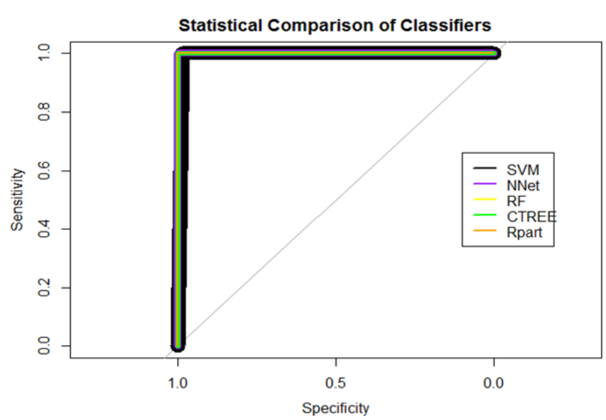

Fig. 2. Area under the Curve of All the Classifiers.

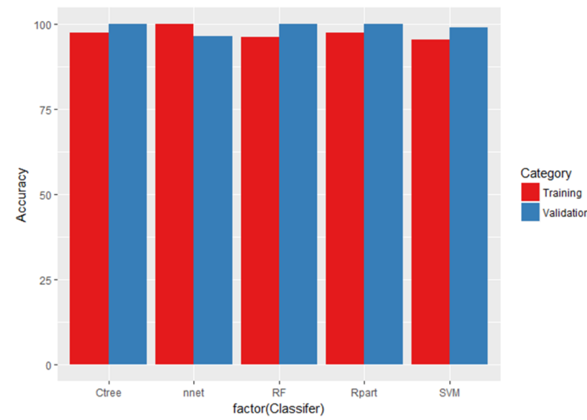

Fig. 3. Comparison of Training and Testing Accuracies of Classifiers.

Table IV shows the accuracies of the classifiers for all the 10 folds individually. Every fold performs a complete run on the data for every technique separately and the result is returned at the end of complete run of the data. Every fold has specific values for the classification of the data. The value 1 shows the maximum accuracy of the classifiers.

Table V shows the Kappa values of the classifiers for all the 10 folds in a 10-fold cross validation process. Results show that in each iteration, as the values of training and testing data are changed, so the results for the evaluation of algorithms are also changed accordingly.

TABLE. IV. ACCURACIES OF CLASSIFIERS FOR 10-FOLD CROSS VALIDATION

Folds	RF	SVM	RPART	CTREE	NNET
Fold01	1	1	1	1	1
Fold02	1	0.9722	0.9722	1	0.9722
Fold03	0.9722	0.8947	0.9210	0.9444	1
Fold04	1	1	1	0.9722	0.9729
Fold05	1	0.9722	0.9722	0.9722	1
Fold06	1	1	1	0.9722	1
Fold07	1	1	1	1	0.9722
Fold08	1	0.9722	1	1	1
Fold09	1	0.9722	0.9722	1	0.9729
Fold10	1	1	1	0.9736	0.9722

TABLE. V. KAPPA STATISTICS OF CLASSIFIERS FOR 10-FOLD CROSS VALIDATION

Folds	RF	SVM	RPART	CTREE	NNET
Fold01	1	1	1	1	1
Fold02	1	0.9423	0.9423	1	0.9423
Fold03	0.9407	0.7847	0.8403	0.8860	1
Fold04	1	1	1	0.9423	0.9417
Fold05	1	0.9423	0.9423	0.9423	1
Fold06	1	1	1	0.9423	1
Fold07	1	1	1	1	0.9423
Fold08	1	0.9407	1	1	1
Fold09	1	0.9407	0.9407	1	0.9417
Fold10	1	1	1	0.9442	0.9423

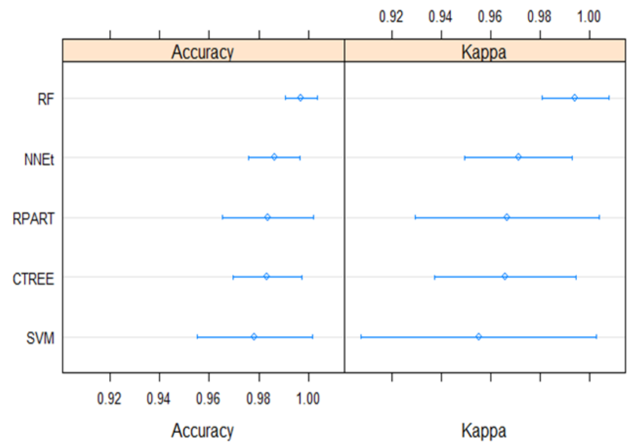

Fig. 4. Comparison of Accuracies and Kappa Values of Classifiers at Confidence Level 0.95.

Fig. 4 shows the comparison of Accuracies and Kappa Statistics values for all the five mentioned techniques. Results show the performance evaluation of Random Forest, SVM, NNet, RPART and CTREE for the classification accuracy of data of the pregnant women. This comparison shows that RF has the highest accuracy value as well as kappa value among all. The accuracy of RF is 0.9972. the Kappa value of RF is also highest as 0.9941. RPART and CTREE have highest training accuracies. Except SVM, all the techniques have maximum validation accuracies and AUC values.

V. Conclusion

In this paper, we show the accuracies of classification algorithms on the dataset of pregnant women for classifying the data into two groups based on the mode of delivery of a woman. The techniques of Support Vector Machines, Neural Networks, Random Forest, Recursive Partitioning and Conditional Inference Tree are applied on the given dataset and the results in the form of accuracy tables, ROC curves and different plots are recorded for further interpretation of the data.

The results show that the tree-based techniques are best suited for the classification of data into normal and C-Section classes as compared to the kernel based approach. Among the tree based techniques, Random Forest shows the maximum accuracy value for the classification of the given data. The Accuracy of Random Forest is highest as calculated 0.9972. The Kappa Statistics for Random Forest is also higher than all the other implemented techniques and is calculated to be 0.9941.

It can be concluded from all the above discussion and the presented results that the technique of Random Forest is best suited for this type of data as it provides the maximum value for accuracy on the given dataset.

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