May – June 2020
ISSN: 0193-4120 Page No. 7929 - 7935

Impact Analysis of Machine Learning Strategies on C-Section Risk Prediction

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***Abstract*:**
Increase in caesarean section (C-Section) rates is a vital issue that needs attention at the global and local level. The major concern of public healthcare is toaddress these issues in terms of quality, equity and accessibility. Effective measures have been proposed and implemented in this work to reduce C-Section rates. The data from cesarean section dataset are classified and analyzed using different machine learning algorithms to predict class accurately in each case. It is very essential and vital to identify which machine learning algorithm classifies accurately the C-section and performs better for risk prediction. Three critical classifiers are considered to implement on the dataset and to measure their efficiency based on the value of various parameters.

Keywords--C-section,Classification, Machine Learning, Accuracy

I. INTRODUCTION

To prevent and treat the potentially fatal maternal complications and foetal complications C-section surgical procedure has been developed.The growth in C-section rates is not well explained by the modification in medical treatment process.The reason for the increase in C-section is women's choice at the point when vaginal birth could end up being risky. A C-segment might be medicinally important when

- not progressing labour
- twins or triplets have occurred i.e. multiple gestations
- severe health concern or the foetus experiences an emergency
- excess fluid or hydrocephalus on the brain of the foetus
- foetus is in the transverse position
- baby is too enormous to even think about traveling through the cervix
- mother is experiencing infectious infection, for example, herpes or HIV that builds the hazard to the baby
- mother is experiencing diabetes or hypertension
- mother has the uterine condition or a fibroid hindering the cervix
- anomalies in placental or umbilical string
- previously mother has conceived an offspring by means of C-segment

Thus, the overall ascent in cesarean area (CS) rates is turning into a significant general wellbeing worry because of potential maternal and perinatal dangers, cost issues and imbalance in get to. Because of the progression of human services frameworks a gigantic volume of clinical databases are made. Here primary spotlight is on the utilization of AI systems of clinical science and bioinformatics field for C-area grouping and hazard forecast. Order is the most usually applied AI system, and uses a lot of pre-arranged directors to build up a model which can characterize number of populations in accounts on loose. The significant objective of the characterization strategy is for foreseeing objective class precisely for each case in info[1]–[3].

II. ALLIED WORK

Numerous creators have executed distinctive AI strategies for arrangement and future forecast. Forecast of liver ailment utilizing Bayesian Classification (BC)by employing Functional Tree (FT)and Naïve Bayes calculations has been finished by Dhamodharan and presumed that Naive Bayes calculation assumes a significant job in anticipating liver maladies. Solanki has utilized J48 and Random tree calculations for order of sickle cell sickness predominant what's more. Random tree providesimproved result that’s why it is associated. Basically, Joshi et al.[4]performed finding & speculation of chest harmful development deploying request instructions, for instance, AdaBoostM1, Logistic Model Tree (LMT), Bayes Net, Stochastic Gradient Descent (SGD), Multilayer Perceptron, Simple Logistic, Attribute Selected, Sequential Minimal Optimization (SMO), Classification by methods for Filtered Classifier,Regression, Multiclass Classifier and J48, they suggested that LMT Classifier provides logically exact end for instance 76 % strong and 24 % cleared out patients. In any case, David et al.[5]have used request methodology for leukemia infirmity desire by using Random tree, K-Nearest Neighbor,Bayesian Network and J48 tree dependent on learning time, error rateandprecision. As demonstrated themby Bayesian count performs well on hand. Regardless, in 2013, Vijayarani and Sudha have taken a gander at the examination of game plan estimations, for instance, Sequential Minimal Optimization, LMTand Multilayer Perceptron computations to envision coronary disease. In a comparable time Kumar’sutilized subbing decision (AD) trees for early assurance of dengue fever. Around a similar time Ranjani and Durairajhave dissected dissimilar data mining requests in social protection section. They have utilized estimations, for instance, J48,Naïve, C4.5 and KNNto portrayal to break down illnesses like AIDS, Heart Disease, Kidney Dialysis, Cancer,Dengue, Diabetes, Hepatitis C and IVF[6]. Connection study discloses that data mining methodology in every single restorative help applications get high precision for instance 97.77% for dangerous development desire and around 70% for IVF treatment through data mining techniques. In 2011, Sugandhi et al.[5], [7]used weka to separate a masses of cascade patient's catalogue. Kannan and Yasodharesearched diabetic patient catalogueby means ofvarious strategies to be explicit Bayes Tree, Network, Random Tree and J48. Assorted gathering systems, for instance, Bayes Network, Radial Basis work, pruning computations andDecision Tree are taken a gander at byYauand Bin for chest threatening development. Jena et al.[8] managed consistent kidney affliction dataset by taking a gander at changed gathering systems, for instance, Conjunctive rule, Naive, SVM, Multilayer perceptron, Decision Table and J48. In like manner Jena et al. further managed risk desire for relentless kidney-disease utilizing unmistakable request & feature decision methodology. Jena et al.[9], [10]have worked on desire for human distress employingapriori computation.

All the above researchers have analyzed the result of various machine learning classifiers on several datasets. But, no one has worked for prediction of cesarean cases. However, Amin and Alianalyzedenactment of administerederudition classifiers for prediction of cesarean section operation. AlsoFergus et al.[11]exhibits how AI can be utilized to anticipate clinical intercession to have cesarean area or not and help to prevent pre-natal deaths.Here, we have applied three number of rule based classifiers in the dataset to study their performance based on various indicators.

III. DATASET DESCRIPTION

The dataset used for our experiment stores the clinical and pathological data about caesarian section test results of a number of women aged between 17 and 40 yrs who are pregnant. The pregnant women have the characteristicsof medical problemsin delivery. The dataset isunivariate whereas the attributes are integer. The dataset consists of 80 number of instances and 6(i.e. 5+class=6) number of attributes

May – June 2020
ISSN: 0193-4120 Page No. 7929 - 7935

TABLE 1:DATASET INFORMATION

S.No.	Name of Attribute	Type	Permissible values
1	Patient Age	Integer	{ 22,26,28,27,32,36,33,23,20,29,25,37,24,18,30,40,31, 19, 21,35,17,38 }
2	Delivery number	Integer	{ 1,2,3,4 }
3	Delivery time	Integer	{ 0,1,2 } -> {0 = on time, 1 = before time, 2 = after date}
4	BP (blood pressure)	Integer	{ 2,1,0 } -> {0 = low BP, 1 = normal BP , 2 = high BP }
5	Status of Heart	Integer	{ 1,0 } -> {0 = apt, 1 = inept }
6	Caesarian (class)	Integer	{ 0,1 } -> {0 = No, 1 = Yes }

IV. CLASSIFIERS AND EVALUATION METRICS

Here, three classifiersnamely Decision Table, Naïve Bayes (NB) andMultilayerPerceptron (MLP) are used for our experiment and they are evaluated with respect to the following critical measures:

- **Accuracy(A):** It tells that how a predictedresult is closed to the actualresult.

  Mathematically it is stated as:

  $$A= \frac{X}{Y},$$

  Where, X=tp + tn

  Y = p + n

  Here, tp= true positive

  tn= true negative

  p= total positive

  n= total negative

  p = tp + fn

  n= fp + tn

- **Sensitivity:** It is defined as a measuring criteria of the proportion of actual positive cases that got predicted as positive.

  Mathematically it is stated as:

  $$\text{Sensitivity} = \frac{\text{True Posi}}{\text{True Positive + Fa}}$$

- **Specificity:**It'snothing but ratio of actual negative cases whichget's predicted as the negative.

  Mathematically it is stated as:

  $$\text{Specificity} = \frac{\text{True Negative}}{\text{True Negative} + \text{False Positive}}$$

- **F-measure:** It is also known as F_1 Score or F-score. The score quantifies the test's precision. To process F-score/F-measure both the accuracy esteem and the review estimation of the test are thought of[12]. Where precision and recall can be calculated as:

  Precision=

  $$(\text{Correct positive results number})/(\text{All positive resultsnum}$$

  Recollection=

  $$(\text{Correct positive results numbers})/_{\text{samples numbers that}}$$

  F-measure is characterized as consonant normal of the accuracy & review. The best estimation of F-measure (immaculate accuracy and review) is 1 and 0 as most exceedingly awful worth.

  Mathematically, F-measure is calculated as:

  F-measure $(F_1)=((recall^{-1}+precision^{-1})/2\ )^{-1} = 2*(\ precision * recall\ ) / (\ precision + recall\ )$

V. RESULT ANALYSIS AND DISCUSSION

The experiment is conducted based on the dataset and the three classifiers are applied to observe their performance behaviour for parameters shown in Table 2.

TABLE2

CLASSIFICATION RESULTS ON VARIOUS PARAMETERS WITH CROSS VALIDATION 10-FOLD

Algorithm	Accuracy(%)	Sensitivity	Specificity	F-measure
Decision Table	67.5	0.613	0.759	0.675
NB	85	0.852	0.847	0.882
MLP	73.751	0.787	0.671	0.793

From Table 2 above, it is seen that Naïve Bayes (NB)algorithm produces the best results in Accuracy, Sensitivity, Specificity, and F-Measure. It results 85% accuracy which is more than the accuracy result of other two algorithms namely Decision Table (accuracy=67.5%) and Multilayer Perceptron (accuracy=73.75%). It also outperforms in Sensityvity(=0.852), Specificity(=0.847), and F-Measure(=0.882) results in comparison to Decision table and MLP.

Thus, in case of prediction the result of Naïve Bayesis more closure to the actual (true) value of the caesarean section (C-Section) data. It plays the major role in C-section risk prediction.In contrast to Naïve Bayes the result of Decision Table is far away from the actual value. ButMultilayer Perceptron classifier produces an average result for predictionof caesarean cases.

The comparison of all the performance metrics for each of the above classifiers is depicted in Figure 1, 2, 3, and 4 respectively.

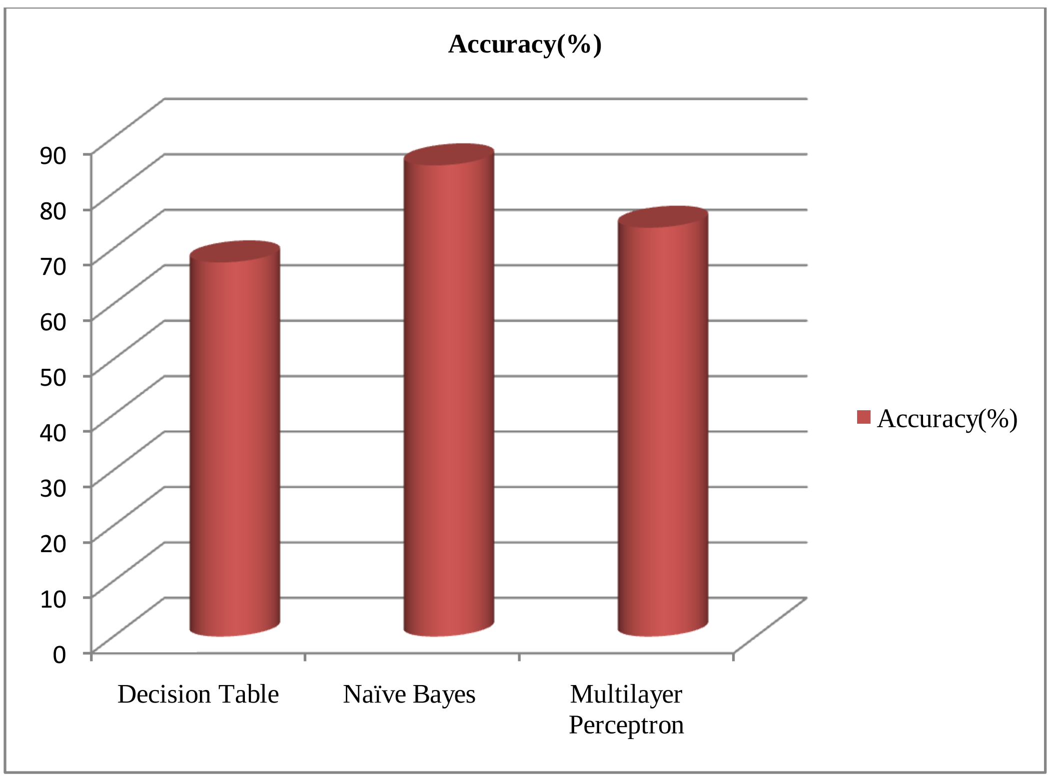

Figure 1: Accuracy Analysis

May – June 2020
ISSN: 0193-4120 Page No. 7929 - 7935

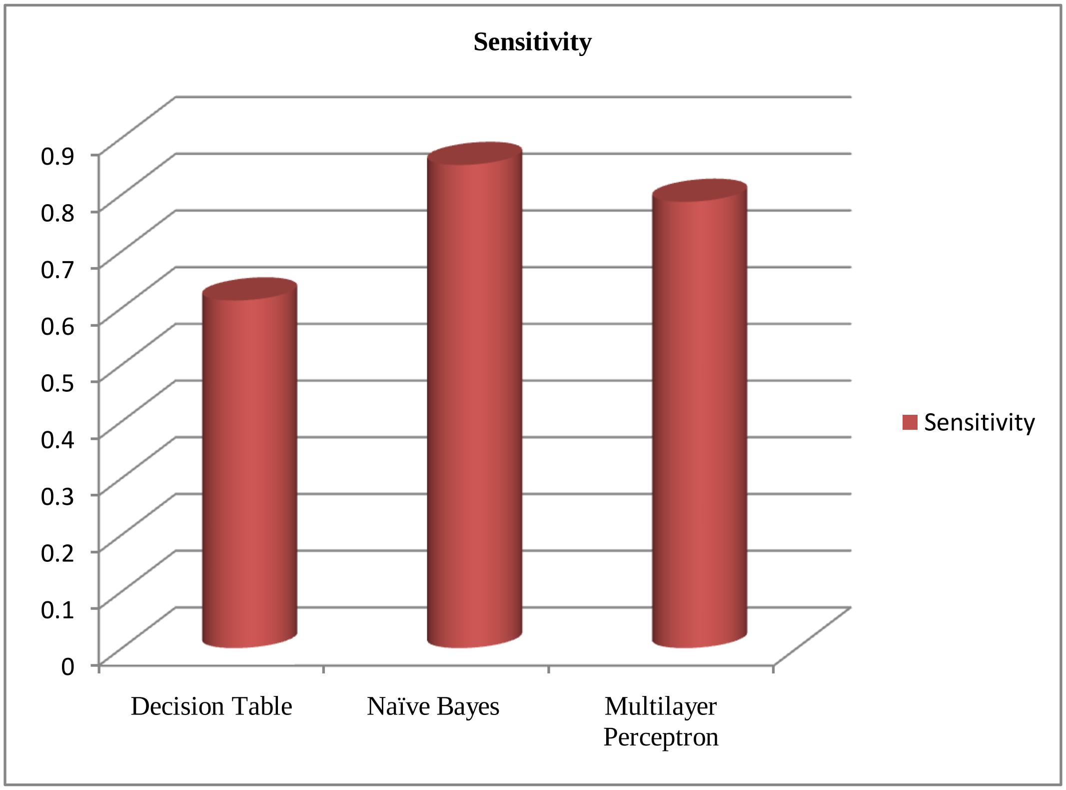

Figure 2: Sensitivity Analysis

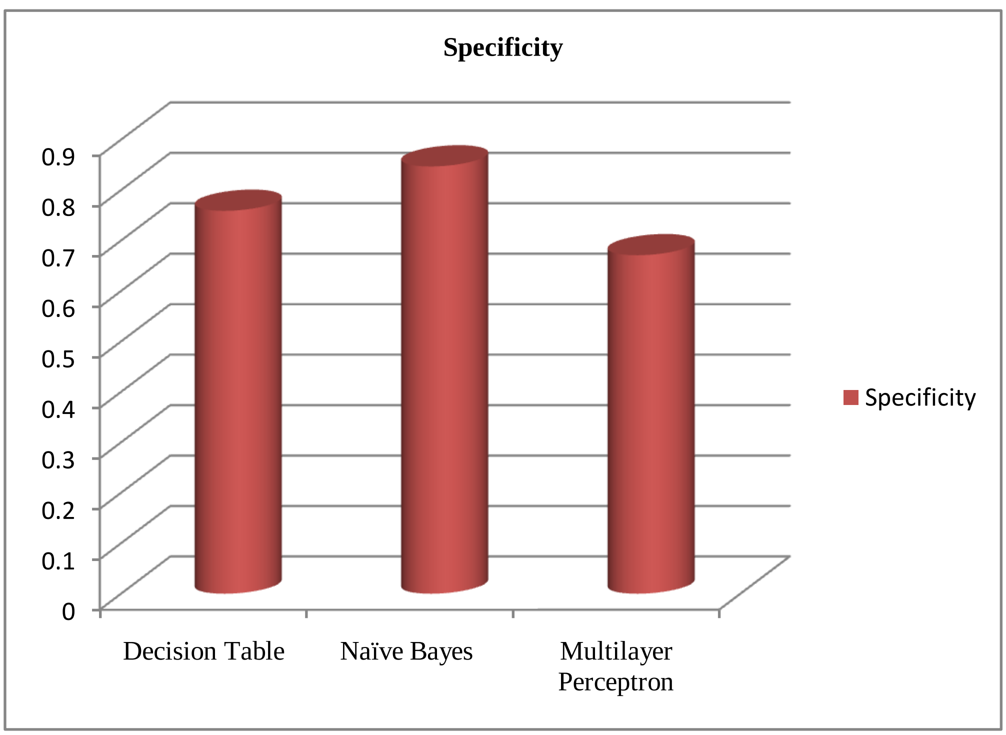

Figure 3: Specificity Analysis

TEST Engineering & Management

May – June 2020
ISSN: 0193-4120 Page No. 7929 - 7935

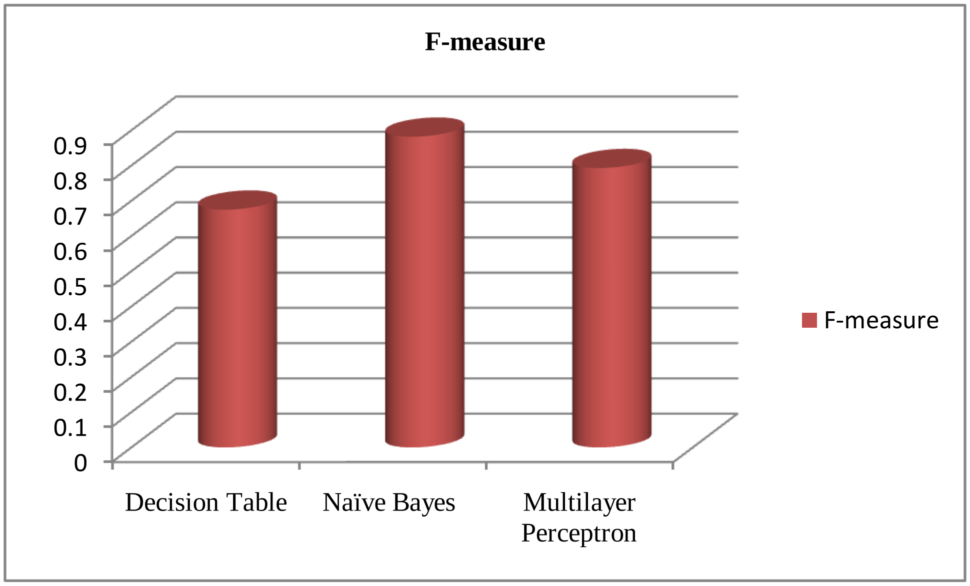

Figure 4: F-measure Analysis

VI. CONCLUSION

The prime objective of the work is to develop efficient machine learning approaches that can differentiate between the caesarean section cases with the normal vaginal deliveries. In this paper, three efficient classifiers namely Naïve Bayes, Multilayer Perceptron and Decision Table have been used. The efficiency of the algorithm to detect caesarean cases have been analyzed and the result in terms of four parameters namely Sensitivity, Specificity, Accuracy and F-score have been computed. Naïve bayes classifier gives better result than others by achieving 85% for Sensitivity, 84% for Specificity, 85% for Accuracy, and 88% for F-score which is better than the two other used classifiers. In future more classification algorithms will be used to enhance the prediction percentage of caesarean cases. To improve the result deep learning approaches will also be used.

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