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PREDICTIVE MODEL FOR CHILD DELIVERY

***Abdulmumini, A. K., Obunadike G. and Jiya E**
Department of Computer Science
Federal University Dutsin-Ma, Katsina State, Nigeria

*Corresponding authors' email: kutigiab@gmail.com

ABSTRACT
Antenatal care is an essential period in which medical experts examines pregnant women to prepare them for proper child delivery. Choosing or knowing the likely mode of child delivery is essential both for the mother and the medical team. It helps in proper preparation for labour and any possible complication that could arise. There are also chances of reducing maternal or child mortality. However, the decision on which of the options is appropriate is sometimes difficult due to several parameters and variable. Analyzing Obstetric and mode of delivery for pregnant woman is tedious, therefore, this work used data from three medical facilities in Katsina State and apply three machine leaning algorithms to predict the most appropriate mode of child delivery. The work was implemented using python programming language software. The result of the work has shown that random forest algorithm performs better with accuracy result as precision was 0.918, recall of 0.715 and 0.896 for Spontaneous Vagina delivery and 0.716 for precision, 0.929 for recall and 0.896 for Caesarian section mode.

Keywords: Safe delivery, Caesarian section, Neural network, Random forest, Naïve Bayes.

INTRODUCTION
From the first day of conception, the mind of every couple is focus on the day of delivery and possible mode. Preparations are made daily for any eventualities that may arise as the estimated date of delivery approaches. Knowing the possible mode helps couples to prepare financially, psychologically and medically however sometimes families are suddenly told of options they never prepared for.
The World Health Organization (WHO) reports large number of death from childbirth in Nigeria and other African countries, these deaths are either result of complete absence of medical attention, not taking decision for a particular mode of delivery early for unforeseen complication. Though there are emergency cases that are sometimes unforeseen, some are avoidable with proper forecast and preparation.
Artificial intelligence has transformed every facet of human life and work. The recent years have also seen the application in wide areas of medical and health sciences like cancer detection systems, leprosy diagnosis, malaria prediction (Kumar, et al, 2014) and outbreak of epidemics. This work analyzed Obstetric and pregnancy factors and use them to predict the most appropriate delivery technique, through the induction of data mining models using real data from General Hospital Dutsin-ma, Federal University Dutsinma Clinic and Comprehensive Hospital Dutsinma Local Government, Katsina State.

REVIEW OF RELATED WORKS
Pereira et al, (2015) developed child delivery mode predictive model using Decision Tree, the generalized linear models, Support Vector machines and Naive Bayes. The system predict types of delivery either cesarean, normal, vacuum or forceps. The most efficient results for statistical metrics, which has best specificity and accuracy, were gotten using Decision Tree.
Khazardoost et al, (2016) did a comparative analysis of Bishop's scores and translabial ultrasound measurements to get outcome of an induced labour. The distance between the Cervical length and fetal head–pubis symphysis were measured using translabial ultrasound. The predictive value of the Bishop's score, cervical length, and fetal head–pubis symphysis distance were determined by using multivariate analysis. The outcome showed that translabial measurements were more accurate method for monitoring labor progress than the Bishop's score.
A detailed work done by Lipschuetz et al, (2020) gradient boosting, Random Forest, Ad- aBoost ensembles and balanced Random Forest to forecast a case of virginal delivery with a case of preceding cesarean section. The work had good performance in term of prediction. Also, Tessmer-Tuck et al, (2014) modeled vaginal delivery with preceding case of cesarean sections using multivariate analysis. This model used two method to evaluate the work: stepwise regression (SR) which had 0.723% of an area under the curve (AUC) and another method reported by earlier research (Grobman, 2007) had 0.757% AUC.
Brandão et al, (2015) used Support Vector Machines, Decision Tree and general linear model to classify the associated side effects ofceasarian delivery. The accuracy level was 93% for Decision tree and 68% for Support Vector Machines.
A related work based on C4.5 classification tree was done by Lakshmi et al, (2016). The work classified the weight and influence of various pregnancy feature to estimating risks in pregnancy and the possible negative effects during gestation.

METHODOLOGY
Study Dataset
This work uses a raw dataset of child delivery from the Dutisnma General Hospital, Federal university Dutsin-ma clinic, and comprehensive hospital Dutsinma. The data contains about 1,160 records with several attributes which are Age, number of delivery, delivery time, blood of pressure, heart problem, number of previous delivery and life or still birth.
The work selected appropriate attributes for modeling base on medical or clinical relevancy for neural network, random forest and naïve bayes model. The work flow methodology is as shown in Figure 3.1.

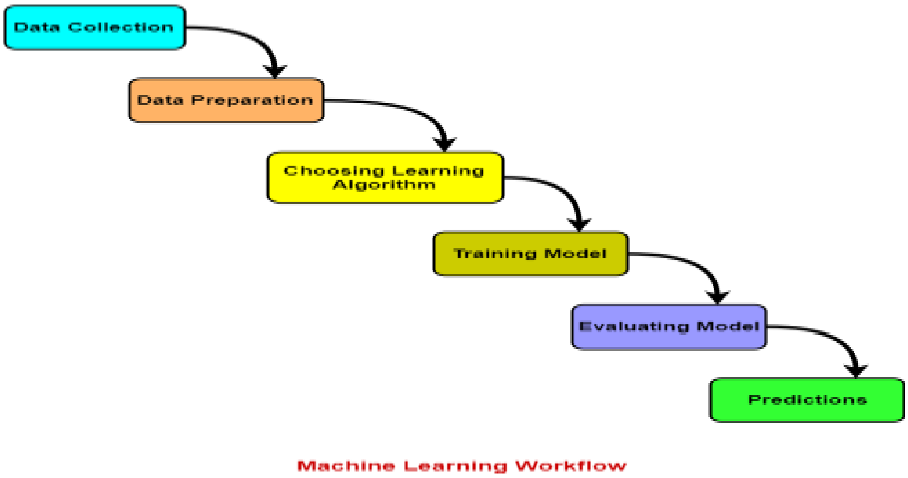

Figure 1: Work Flow Methodology (Fu, et al., 2020).

Data Preparation and Missing Value Replacement

The adequate analysis of data in all kinds of research fields is often hindered by the presence of missing information, a widespread problem that many data analysts commonly face. The occurrence of missing values arises from different reasons such as measurement errors, accidental deletion of recorded values, non-responses, and mistakes in data entry.

This research work impute missing values with mean values for solving the missing value using the command fillna() from NAN.

The record taken from the three hospitals contain about 1160. However, following, since the percentage of the missing value is small and may not alter the result of the work, they were deleted. Table 3.1 shows the attributes, category and values

The fields and attributes

Table 1 Attributes, Category and Values

PARAMETER	CATERGORY	VALUE
Age	Numeric	1—50
Type of clients	Ordinal	Booked, Unbooked
Mode of delivery	Ordinal	SVD, CS
Parity	Numeric	1-15

METHOD OF IMPLEMENTATION

This research made use of Artificial Neural Networks, Random forest and Naïve Bayes available in Python data mining tool by importing their libraries. Neural networks have been shown in many researches to handle complex data sets and in some cases have performed better than traditional statistical methods, which this research also prove that from the result gotten after the implementation. Besides, the neural networks model has been used for feature subset selection to identify the most relevant factors in each developed model. Results obtained were incorporated with the qualitative methodology afterwards to build a comprehensive model that has better performance and better interpretability by end-users.

During the process of training the predictive models, the data was first examined for outliers and missing values. After the outlier analysis, these values was replaced with appropriate values to minimize the effect on incorrect predictions. The models was trained and tested for the validity and accuracy.

In this work, python programming was used to write a program for model prediction of child mode delivery using Neural network, Random forest and Naïve Bayes algorithms.

RESULTS PRESENTATION AND ANALYSIS

The Neural network model developed in python

The data analysis in table 2shows the mean, standard deviation 25%, 50%, 75% and the maximum of the dataset.

Table 2: The dataset characteristic

parameter	age	Number of delivery	Delivery time	blood of pressure	heart problem	Number of previous delivery	life or still birth
						0.487177	
mean	36	27.687500	1.662500	0.637500	1.000000	0.000000	1.000000
std	6	5.017927	0.794662	0.815107	0.711568		0.711568
min	20	17.000000	1.000000	0.000000	0.000000	0.000000	0.000000
25%	29	25.000000	1.000000	0.000000	0.750000		0.750000
50%	34	27.000000	1.000000	0.000000	1.000000	0.000000	1.000000
75%	38	32.000000	2.000000	1.000000	1.250000		1.250000
max	42	40.000000	4.000000	2.000000	2.000000	1.000000	2.000000

The correlation graph for the independent and dependent data for all the attributes is shown in figure 2

Figure 2 correlation graph for the independent and dependent variables

The graph in figure 2 indicates the relationship between all the parameters used which the disgonal is indication 1.0. The number of previous delivery is plotted against the age and it shows that those between the age of 17 and 20 are having less number of children they have given birth to, starting from 21 to 40, the birth number increases from 1.00 to 3.00. by indication, The older the more likely the number of children.

The graph in figure 3 was generated in Python using data mining tool called matplotlib and it indicates the relationship between number of previous delivery and the age of the mother. Age 17 to 20 indicated that the number of previous delivery is very low then it increases as the age increases and 37 to 40shows that we have high number of previous delivery.

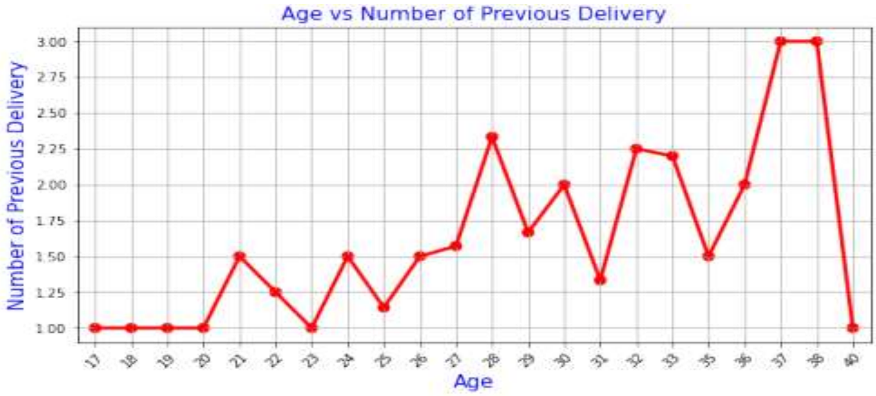

Figure 3: Graph of number of previous delivery against Age

Random forest and Naïve Bayes Model accuracy parameter
The model accuracy are given in the table 3-4, which include True Positive, False Positive, Precision, Recall, F-measure, MCC, Receiver Operation Curve values, and PRC curve value for each of the algorithms Random forest, Neural Network and Naïve Bayes).

Table 3: Random forest model accuracy metric table

class	TP Rate	FP Rate	Precision	Recall	F-measure	MCC	ROC curve	PRC curve
SVD	0.635	0.112	0.863	0.635	0.731	0.536	0.841	0.875
CS	0.888	0.365	0.686	0.888	0.774	0.536	0.841	0.785
Weighted Avg.	0.755	0.232	0.779	0.755	0.752	0.536	0.841	0.833

Table 4: Naïve Bayes model accuracy metric table

class	TP Rate	FP Rate	Precision	Recall	F-measure	MCC	ROC curve	PRC curve
SVD	0.687	0.540	0.586	0.687	0.633	0.151	0.582	0.572
CS	0.460	0.313	0.569	0.460	0.509	0.151	0.582	0.578
Weighted Avg.	0.580	0.432	0.578	0.580	0.574	0.151	0.582	0.575

Figure 4 shows the graph for class-based accuracy result for the three classifiers, and it is discovered that random forest performed better than all the other two algorithms precision was 0.918, recall of 0.715 and 0.896 for Spontaneous Vagina delivery and 0.716 for precision, 0.929 for recall and 0.896 for Caesarian section mode

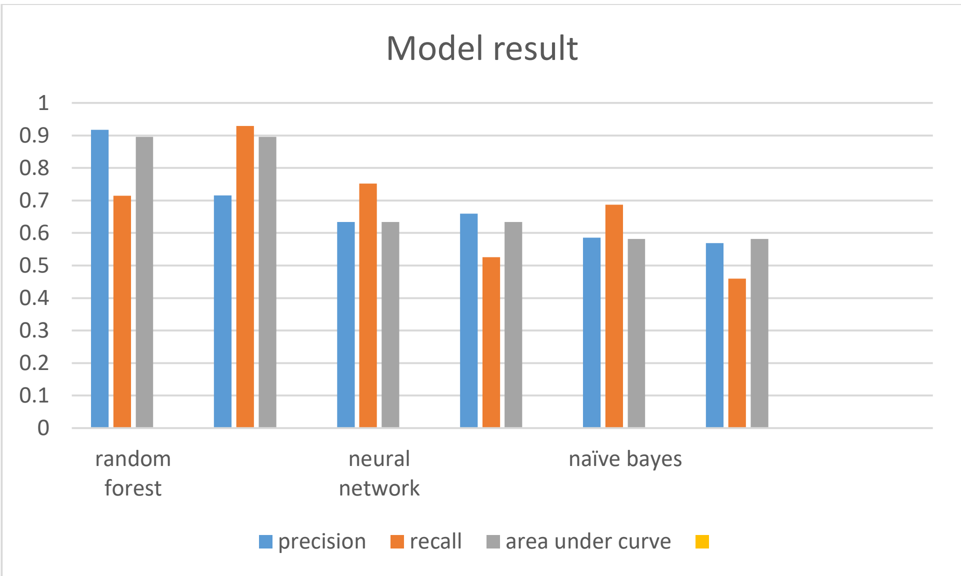

Figure 4: Accuracy level Graph

CONCLUSION

By working with the aim and objectives of the research work which is comparison between three machine learning algorithms Random forest, Naïve bayes and Neural network were examined where Python programming was used for Neural network random forest and naïve bayes, these machines tried to perfectly predict the child delivery mode and random forest give the best result as precision was 0.918, recall of 0.715 and 0.896 for Spontaneous Vagina delivery and 0.716 for precision, 0.929 for recall and 0.896 for Caesarian section mode. 7

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