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Artificial Intelligence Model for Predicting Maternal Blood Clots in Childbirth

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Abstract
Blood clots are gradually becoming a regular case and inevitable, among pregnant women during childbirth, which often leads to death. Pregnant women are vulnerable to diseases that might lead to blood clots in childbirth. This is because pregnancy is a delicate stage and associated with several abnormalities such as swollen legs, pale eyes, change of skin color, spotting, waist pain, weight loss, and vomiting, as observable in most pregnant women. This study is aimed at developing an artificial intelligence (AI) model for predicting possible maternal blood clots in childbirth that could lead to severe issues or even death. The paper illustrated a Machine Learning (ML) approach based on various algorithms in the design of an AI model for predicting abnormal blood clots resulting from untreated ailment, postpartum hemorrhage, and Caesarian delivery that may block blood vessels and reduce the intake of oxygen. The mean square error (MSE) of the new model was 96.6 percent and the results obtained showed that the model can be used to predict the critical blood clots in pregnant women during and after childbirth. The study also showed that an increase in the number of untreated ailments in pregnant women is proportional to an increase in the risk factor of a maternal blood clot at childbirth.

Keywords: *Maternal blood clots, Machine learning approach, Artificial intelligence, Childbirth, Predicting model*

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1. Introduction

Bleeding in childbirth is a natural phenomenon that is often experienced by all mothers irrespective of the childbirth mode of delivery adopted. However, choosing the wrong mode of delivery may pose some serious issues for both mothers and babies such as fetal termination, excessive bleeding and breathing problems (Hendler *et al.*, 2017) The study only identified bleeding as a natural phenomenon without any consideration for possible clots that could result from it. An increase in the mortality rate of pregnancy women has been traced and attributed to critical blood clots during childbirth. This is because pregnancy is vulnerable to several health issues and untreated illnesses in pregnant women in most cases result in severe blood clots that can lead to death at childbirth.

Blood clots can travel through the bloodstream to the major organ such as the brain, causing a stroke. It is typically diagnosed through imaging tests such as ultrasound, magnetic resonance imaging, and cathode ray tube scans. However, in this paper, improved technology of testing, and predicting the likely blood clotting in mothers at childbirth is introduced to minimize maternal death at childbirth. Muhammad et al. (2020) carried out research that determined the best mode of child delivery using machine learning approach for analyzing and predicting the preferable mode of childbirth instead of manual decision by physicians. The study's shortcoming is that it is limited only to the prediction of the best mode of childbirth and was not meant to solve problems related to blood clots during childbirth. Pregnancy abnormalities associated with COVID 19 could cause several complications such as genetic disorders resulting in blood clots or an increase in the risk of hyper-coagulation states (Servante *et al.*, 2021). COVID-19 causes some patients to develop a severe pro-inflammatory state which can be associated with a unique coagulopathy and pro-coagulant endothelial phenotype. It can also lead to arterial thrombotic and microvascular thrombotic disorders (Wool and Miller, 2020). The research considered only COVID 19 as an illness that could result in blood clots. Individuals with diabetes,

chronic lung, inflammation, and vascular disease health issues are considered at higher risk of adverse COVID-19 outcomes that are likely to result in severe blood clots in the lungs (Papadopoulou *et al.*, 2021).
COVID 19 patients are prone to disease severity due to abnormal blood coagulation introduced by the virus as reported from the coagulation profiles of hospitalized COVID 19 patients in Addis Ababa, Ethiopia (Araya *et al.* 2021)

Lakshmi *et al.* (2015) conducted research that aimed at monitoring the health of pregnant women during pregnancy to protect them from possible disease vulnerability and complications during childbirth. The research limitation was that the issue of blood clots, which poses a major concern during child delivery was not discussed. Poonguzhali *et al.* (2019) carried out research that is designed an embedded blood coagulation detecting system that hinges on magnetic and optical detection methods. The research shortcoming is that it never discussed if the system has the capability of predicting blood clots for pregnant women during childbirth. Aria *et al.* (2019) carried out research on the technological advancements in blood coagulation measurement for diagnostic testing that focused on measuring the electrochemical, optical, and mechanical parameters of clotting blood. Machine learning techniques were not used as one of the advanced technological tools in the research study and the research study result presented never explained if the system could be used for predicting future blood clotting during childbirth. Sanders (2007) carried out research that detects blood clotting through the application of neural network to overcome the threat of invasive surgery that often leads to blood clots. Its limitation was that it cannot be used to predict the possible blood clots in the future. Sean *et al*. (2019) conducted research on the acute ischemic stroke regarding blood clots without precise description on the cause of blood clot to women at childbirth. Akazawa *et al.* (2021) conducted research that focused on vaginal birth postpartum hemorrhage prediction. The research did not discuss the issue of blood clots after childbirth. Support Vector Machine (SVM) algorithm type of machine learning is considered unique with respect to the capacity to handle multiple continuous and categorical variables in n-dimensional space, results accuracy, and memory management compared to other types of machine learning algorithms (Mangasarian, 2001). This paper, therefore, developed an artificial intelligence model to predict any possible blood clots to pregnant women at childbirth.

2. Materials and methods

This section describes all the materials used in carrying out the research exercise. Also, the strengths and weaknesses of several machine learning algorithms were discussed in detail and extrapolated for building the maternal blood clot prediction model at childbirth. The materials used for this study were:

a. C Language
b. Python Language
c. ASP.NET Framework
d. 2019 Microsoft Visual Studio IDE
e. MATLAB Application
f. WEKA Application and
g. Machine Learning Algorithms
h. Medical records of pregnant women obtained from Federal Medical Centre Owerri and Our Lay's Hospital Umuowa Orlu, Imo state.

In this paper, several machine learning algorithms were considered for maternal blood clot prediction and detection at childbirth. The integration of the individual algorithm gave birth to the research model of this paper. In the design of the proposed AI model for predicting blood clots at childbirth, parameters such as age, weight gain, health state before pregnancy, present health state, present month, family history, gestational diabetic presence, and blood pressure are considered. The model architecture is depicted in Fig. 1.
[A] K-Nearest Neighbor Algorithm (KNN)
[B] Gaussian Naïve Bayes Algorithm (GNB)
[C] Support Vector Machine Algorithm (SVM)
[D] Decision Tree Algorithm (DT)
[E] Logistic Regression (LR)
[F] Stack Classifier (SC)

[A] K-Nearest Neighbour Algorithm

The K-nearest neighbour algorithm is applied in this study because of its efficiency in predicting test results while fitting in the algorithm training dataset on sample results. Nine months of pregnancy period was considered in our dataset's selection. In this study, M_1denotes the month of conception M_2through $M_8$are taken as child formation months while M_9denotes the delivery month. The research experiment is limited to women with sixth childbirth. Therefore, W_1 denotes a woman with first childbirth experience, W_2denotes a woman with second childbirth experience, W_3 denotes a woman with third childbirth experience, W_4denotes a woman with fourth childbirth experience, W_5 denotes a woman with fifth childbirth experience, and finally W_6denotes a woman with sixth childbirth experience. KNN–algorithm model for predicting possible blood clots at childbirth is shown in Algorithm 1.

KNN Clot Prediction Algorithm 1

Step 1: Input Unit:

Define the acceptable K-nearest neighbour range of value for blood clot $(-0.5 \leq K \leq 0.5)$

Define parameters for blood clot prediction.

$(B[C], nB[C]) \Rightarrow W_1, W_2, \dots W_n;\ M_1, M_2, \dots, M_n;\ A_{r-1+n}, A_{r-2=n}, \dots A_{r+n-m}$

A is age, r is range, n is number of childbirths, m is mortality rate at childbirth

$T_d \leftrightarrow$ Training dataset of $B[C]$ for $W_{1\_}W_n$

$B[C] \rightarrow Blood\ clot;\ nB[C] \rightarrow non - blood\ clot$

Step 2: State condition for clot detection and prediction

Calculate the Euclidean distance of K numbers of neighbours for blood clot and non-blood clots.

$if\ E_d \propto \frac{1}{B[C]}\ then\ Knn\ for\ blood\ clot = 0$

$Else\ Knn > 0.5$

This means the impending blood clot is high and demands urgent medical attention to avert the occurrence.

Step 3: Determine the number of data points in each K-neighbours category through count and assign the new data points to the category for which the number of K neighbour is maximum.

Step 4: Output Unit:

Compare Knn input value and predicted value.

$if\ Knn = 1$. Then most similarity features exist, and blood clot is a must.

$Else\ B[C]\ is\ uncertain.$

Step 5: KNN Algorithm for blood clot is ready for use.

[B] Gaussian Naïve Bayes algorithm (GNBA)

This machine learning algorithm is a powerful tool in computing blood clots with continuous valued features. The probability of predicting $B[C]$ variable x occurring from class A distribution and $nB[C]$ variable y not occurring from class B distribution at a particular month of a woman's pregnancy before childbirth is computed using Gaussian Naïve Bayes Classifier to estimate the parameters needed for blood clot classification. It is assumed that the continuous values associated with each class are distributed according to a normal (Gaussian) probability distribution. Therefore, the likelihood of the $B[C]$ features is presented in Equation (1).

$$P(B[C]|\, nB[C]) = \frac{n}{\sqrt{2\pi\sigma_y^2}} exp(\frac{(x_n - \mu_y)^m}{2\sigma_y^2}) \qquad (1)$$

GNB Clot Prediction Algorithm 2

1 Input: Naïve Bayes Probability for blood clot prediction is stated thus:

2 $P(B[C]|\, nB[C]) = \frac{P(B[C] \cap \overline{nB[C]})}{P(B)} = \frac{P(B[C])\ .\ P(nB[C]|B[C])}{P(nB[C])}$ (2)

Prediction $(x) = \arg\max p(B[C]|nB[C])$

Note that $\max p(B[C]|nB[C])$ returns the maximum probability of $nB[C]$ while $\arg\max p(B[C]|nB[C])$ returns the $B[C]$ with the highest probability.

3 $P(B[C]) \rightarrow$ The probability of $B[C]$ occurring.

4 $P(nB[C]) \rightarrow$ The probability of $nB[C]$ occurring

5 $P\left(B[C]\ \cap\ \overline{nB[C]}\right) \rightarrow that\ the\ degree\ of\ clot\ is\ higher$

6 Blood clot classifier prediction model:

7 (Gaussian) $\frac{\pi_i \frac{1}{\sqrt{2\pi\sigma_{i,j}^2}} e^{-1/2(\frac{B[C]_i - \tau B[C]_j}{\sigma_{i,j}})^2} . P(B[C]_j)}{P(B[C])}$ * (Naïve) $\frac{\pi_i P\left(\left(B[C]|nB[C]\right)\right) . P(nB[C])}{P(B[C])}$

8 Assume a new data from a pregnant woman then apply (Bayes) analysis.

9 (Bayes) $\frac{P(B[C]_{el}|nB[C]_{el}) . P(nB[C])}{P(B[C])}$

10 $if(B[C]_{el} > nB[C]_{el})$
Then the likelihood of the clots is high, and the algorithm will give an alarm for critical attention.

[C] Support vector machine algorithm (SVM)

The support vector machine was considered among the algorithms implemented in this paper, because of its inherent feature to handle multiple continuous variables in line with predicting blood clots at childbirth because it has best result accuracy. The SVM performance prediction accuracy for this study is 95%. The high percentage accuracy of SVM for the classification of pregnant patients indicates the high performance of the machine learning algorithm for predicting possible blood clots at childbirth. This optimal performance value of SVM revealed that it can effectively handle n-Dimensional data in childbirth to predict any possible blood clots.

[D] Decision tree algorithm (DT)

The Decision Tree (DT) algorithm is a revolutionized supervised learning algorithm that is used in solving regression and classification problems. In this research, it is used for predicting possible blood clots on a woman at childbirth through the application of a machine learning training data model. We denote the decision tree root of this paper to be the pregnant woman while the decision node is the delivery type and a good number of delivery experiences. Mathematically Decision Tree (DT) for multiple data attributes is represented as:

$$D(W_c, S_d) = \sum_{a=20}^{N} P(B[C]) * D(B[C]) \qquad (3)$$

where W_c is the woman's current state, S_d is the selected data (attribute), a is the age, N is the number of time a woman has a childbirth, $P(B[C])$ is the probability of the blood clot, and $D(B[C])$ is the blood clot decision.

$$if(W_c == S_d)\ B[C] < 0\ and\ will\ not\ occur$$

$$else\ if(W_c > S_d)B[C] > 0\ and\ must\ occur\ at\ childbirth$$

Table 1 has necessary attributes for a pregnant woman decision for clot or none clot.

Table 1: Pregnant patients trained / selection data analysis.

B[C] Experience	Age (W_c)	Pregnant		Number of Childbirth	Selected attribute (S_d)	
		Yes	No		Age	Number of Childbirth
Nil	38	1	0	4	25	2
Nil	45	1	0	6	30	1
Nil	43	1	0	5	32	3
Nil	34	1	0	2	22	1

[E] Logistic regression (LR)

Logistic regression is employed in this work because it is efficient in predicting discontinuous variables such as high or low, yes or no, negative or positive, zero (0), or one (1). This is because the AI model is designed to give high for predicting blood clots and low for no blood clots occurrence. In this paper, logistic regression was implemented with the standard steps stated below using Python.

a. Pre-processing pregnant patient data
b. Fitting logistic regression to train the pre-processed data.
c. Predicting the test result for clot
d. Test accuracy of the result using confusion matrix
e. Visualizing the test set result of the pregnant patient.

[F] AI model framework

The AI model for predicting maternal blood clots is a consortium of several machine learning algorithms already discussed in this paper. It adopts a learning technique in which the best prediction of multiple classifiers is combined to generate a new training set for a meta-classifier. The prediction model showed an optimal result of 99.2 % accuracy for predicting maternal blood clots at childbirth in this study. Figure 1 depicts the architectural framework of the AI model. The Gaussian Naïve Bayes (GNB) is used as a filter in the design of the proposed AI architecture because of its multi-class prediction features and efficiency in real-time predictions.

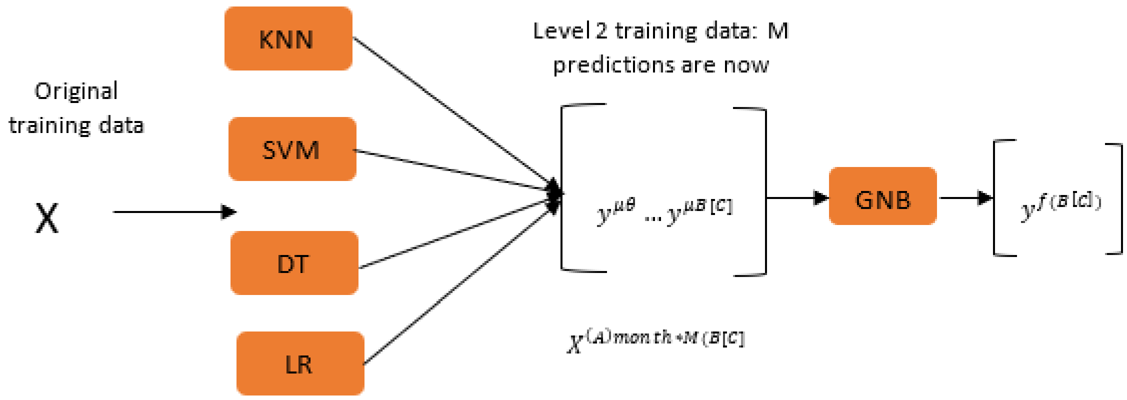

Fig. 1: Architectural framework of an AI-prediction model

2.2 Machine learning algorithms evaluation

The multiple evaluation measures were deployed in the evaluation of all the Machine Learning algorithms implemented to validate the new model. The accuracy and precision of the most accepted algorithm with the final prediction rule are determined by applying the rule regulating each algorithm on pregnancy datasets for predicting the risks of blood clots during pregnancy as stated in equations (4) to (7). The main goal of the evaluation process is to achieve efficient prediction accuracy, precision, and sensitivity in every predicted blood clot at childbirth. ML algorithm evaluation was implemented with the help of mean square error (MSE). The prediction rule on pregnancy data is shown in Figure 2.

$$Accuracy\ (A) = \frac{Total\ Prediction\ (TP) - False\ Prediction (FP)}{Total\ Prediction\ (TP)} \quad (4)$$

$$Precision\ (P) = \frac{True\ Positive\ Prediction\ (TPP)}{True\ Positive\ Prediction\ (TPP) + False\ Positive\ Prediction (FPP)} \quad (5)$$

$$Sensitivity\ (S) = \frac{True\ Positive\ Prediction\ (TPP)}{True\ Positive\ Prediction (TPP) + False\ Negative\ Prediction\ (FNP)} \quad (6)$$

$$MSE = \frac{1}{N_{Pregnant\ Patients}} \sum (B[C]_{True} - B[C]_{Predicted})^2 * \frac{100}{1} \quad (7)$$

Where $B[C]_{True}$ is the blood clot output, $B[C]_{Predicted}$ is the predicted output, and $N_{Pregnant\ Patients}$ is the number of sample patients.

$$MSE = \frac{1}{700}[200 - 174]^2 * \frac{100}{1} = 96.6$$

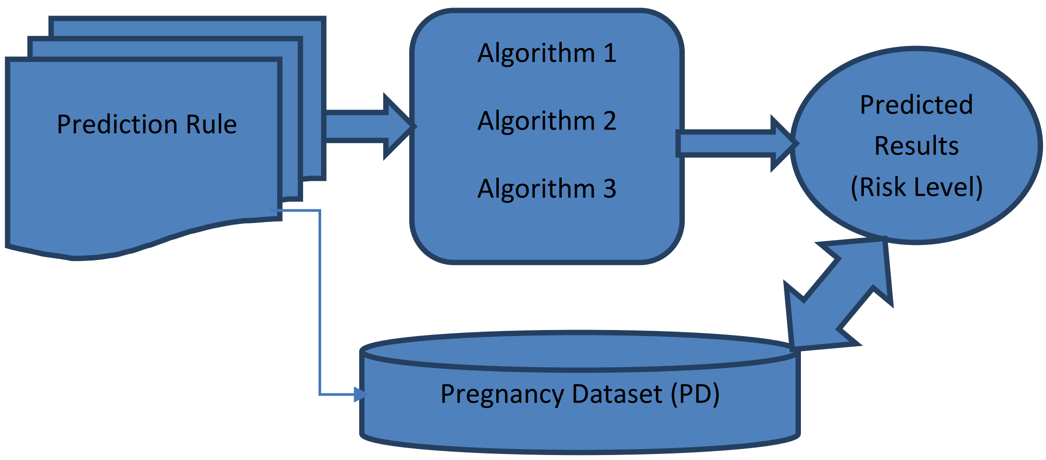

Fig. 2: The application of prediction rule on pregnancy data

3. Results and discussion

The research survey findings are depicted in Table 2. In case 1 of Table 3, there is 42 percent of maternal blood clots at childbirth due to the number of untreated illnesses in pregnant patients. This is the study with the least percentage risk factor for maternal blood clot at childbirth. In case 7 of Table 3, there is 77 percent of maternal blood clot at childbirth due to the number of ill pregnant patients in the study. This is the study with the highest risk factor for maternal blood clot at childbirth and is due to the number of ill pregnant women involved. The research result concludes that the risk factor for blood clot is proportional to the number of pregnant women with health issue which most times block the veins and arteries that results to dizziness due low oxygen intake. The outcome often deterriorate to stroke or even cause death. Therefore, for the risk factor to be minimized every identified ill-health on a pregnant woman is either treated or controlled using this paper prediction model for maternal blood clots in childbirth.

Table 2: Parameters for predicting blood clots

S/N	Parameter	High	Low
1	Personal details		
	Age	1	0
	Weight on conception	1	0
	Present weight	1	0
2	Health information		
	Health state before pregnancy	1	0
	Present health state	1	0
	Weight gain	1	0
	Blood pressure	1	0
	Gestational diabetic presence	1	0
	Spotting	1	0
3	Family History		
	Mother / Sister with blood cloth experience	1	0
	Mother / Sister gestational diabetes	1	0
	Mother / Sister blood pressure during pregnancy	1	0
	Mother / Sister pregnancy abnormality	1	0

Table 3: Summary of reported cases of pregnant women with thrombotic issue in childbirth

Case	Study Number	Women with Health Issue	Women with no health issue	Pregnancy Women	Women with thrombotic issue	Risk factor
Case 1	550	230	320	550	230	42
Case 2	840	560	280	840	560	67
Case 3	980	680	300	980	680	69
Case 4	1010	670	340	1010	670	66
Case 5	745	482	263	745	482	65
Case 6	990	610	380	990	990	62
Case 7	418	320	98	418	320	77
Case 8	630	380	250	630	380	60
Case 9	710	435	275	710	435	61
Case 10	380	240	140	380	240	63
Total	7253	4607	2646	7253	4607	

Fig. 3 and 4 respectively depict the results of a predicted blood clot in pregnant women using the newly developed AI model based on machine learning for predicting. Also, due to the limited availability of time and resources, only 700 data of pregnant women were investigated through the questionnaires and records from the medical experts. According to Figure 3, the legend of the graph red indicates blood clots, green indicates no blood clot, and blue indicates the determinant factors for clotting. The red dots are increased beyond the value of 0.5 on both the patient clotting attribute axis and clotting prediction rate axis. The 0.5 on the graph depicts 50 percent on both axes. This indicated critical blood clots in a woman after childbirth. This kind of clot in most cases, claims lives. The essence of the AI predicting model is to predict a possible blood clot to avert impending doom or degeneration that could take life in child delivery. Figure 4 is a predicted maternal blood clot AI-model confirmation analysis. It has red dots surpassing 0.5 on the clotting prediction rate, which implies the blood clot of a patient. The 0.5(50%) implies that the predicted result is critical and most likely to occur in a pregnant woman after childbirth and must be checked. Even with the alert on the clotting prediction rate, the patients' clotting attributes reported normal, which implies no danger of clots at childbirth. This is because the distributed blood clot prediction analysis hinges on two important variables, the clotting prediction rate and patient clotting attributes for predicting accuracy. The clotting factor represented by blue dots is widely spread and this is critical concern that maternal blood cloth is most probable. The AI prediction model operates in a way that the clotting rate, patient clotting attributes, and clotting factors variables are considered for every clot prediction made for a pregnant woman against delivery time. Also, the height of the clotting factor is evidence of a future blood clot. The new system prediction accuracy is found to be 99.2%. The absolute risk of thromboembolic complications in pregnant women without COVID-19 is 0.1% (Rabinovich *et al.*, 2019). Estimates of the incidence of disseminated intravascular coagulation in pregnant women and between 0,03% to 0.35% (Koumoutsea et al., 2020). The study suggests that the blood clots risk factor increases with the number of untreated illnesses in pregnant women. This implies that,

$$r_f \infty u_i \tag{8}$$

$$r_f = ku_i \tag{9}$$

where, r_f is the risk factor, u_i is the untreated illnesses, and k is the constant of proportionlity.

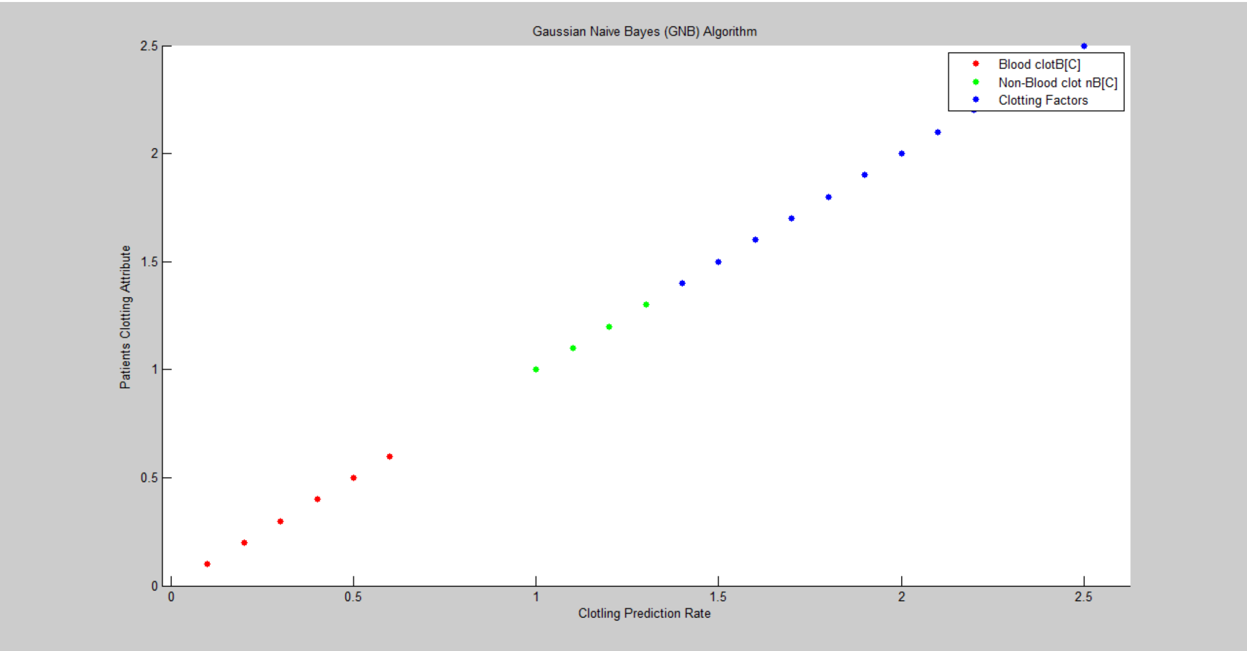

Fig. 3: Predicted maternal blood clot of the AI model

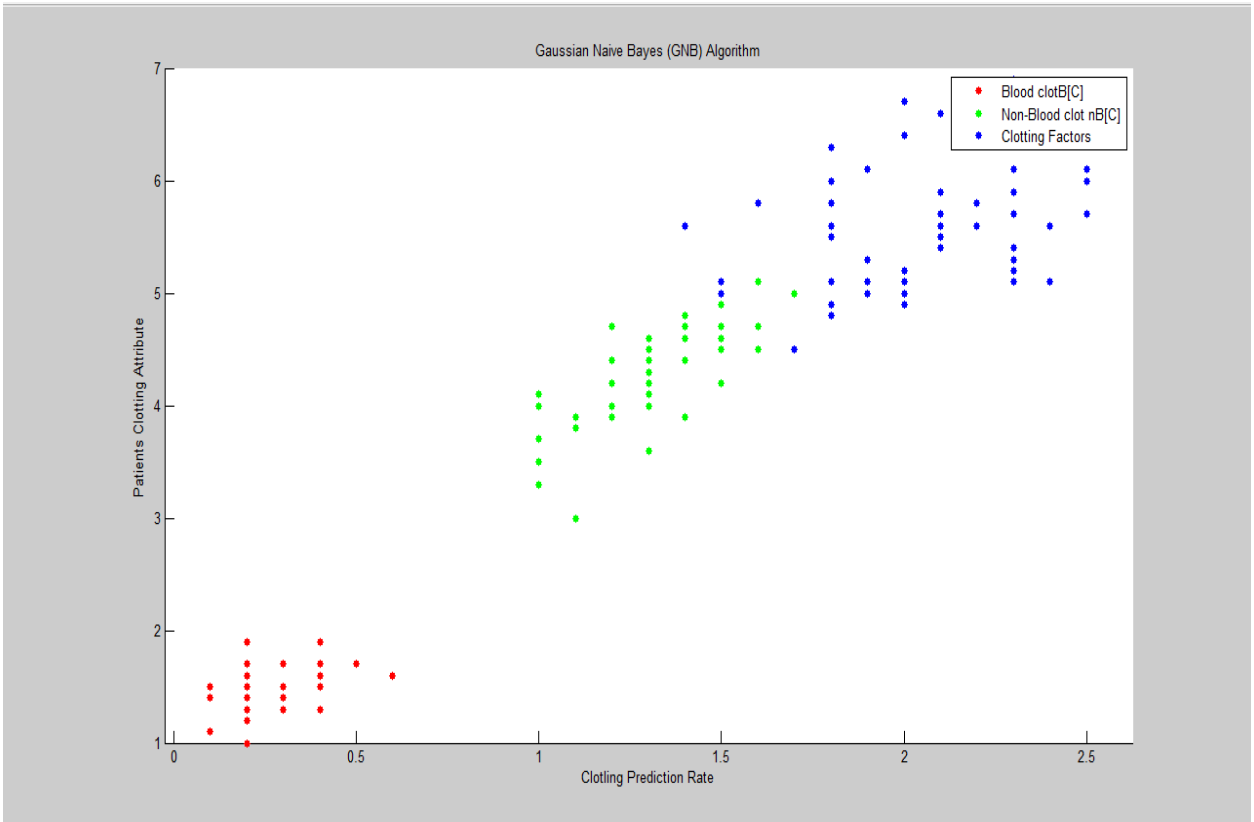

Fig. 4: Predicted maternal blood clot AI-model confirmation analysis

4. Conclusion

A maternal blood clot is indeed a great concern in our world today due to lives that have been lost through it. It is increasingly observed that a significant number of pregnant women experienced severe complications during and after childbirth due to maternal blood clots and in most cases, the situation is fatal. However, it is now imperative that a system is developed to control, monitor, and prevent the impending doom facing pregnant women at childbirth due to critical clots. In this paper, an AI prediction model based on machine learning was developed for predicting the possible maternal blood clots at childbirth. The result of the mean square error (96.6 percent) showed that the system is efficient in predicting possible blood clots in pregnant women at childbirth. The study showed that the risk of thrombotic events is higher in pregnant women with untreated health issues than in pregnant women with no health issues. Therefore, it is recommended that future direction should include pregnant women from different demography datasets of unwanted pregnancies and aborted babies.

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