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Interpretable Using Feature Importance, SHAP and LIME for Caesar's Prediction

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Abstract **- Birth is a process that is very feared by a pregnant woman from extreme pain, death, and childbirth. If the delivery has problems, a cesarean section is performed, but this requires a doctor's decision to analyze the prospective mother's medical record. From the medical record data, a method with Machine Learning (ML) is needed to be able to see which symptoms or features a Caesarean section was performed or not. The model for this analysis used Feature Importance, SHapley Additive exPlanations (SHAP), and Local Interpretable Model-Agnostic Explanations (LIME) and the results from the model tests Meet Fault and Genital and Pelvic are the highest of the features that are very influential in Caesar's predictions. The models that are very easy to understand in this test are Feature Importance and SHAP.**

Keywords **– Prediction, Caesar, Interpretable, Feature Importance, SHAP, LIME.**

INTRODUCTION

Birth is a process that all women must go through after pregnancy and becomes an experience that will not be forgotten for the rest of their lives [1][2] but becomes a psychiatric disorder that is fatal for a prospective mother [3][4]. Before giving birth, many things must be prepared that the candidate is worried about, from defects in the baby to death [5][6], especially in the process of giving birth whether by normal or cesarean section. If a normal birth means there are no problems for the prospective mother and child, the expectant mother is afraid of experiencing excruciating pain and the process takes a long time [7].

By cesarean section, it is recognized that it is safer and does not frighten the expectant mother, but the process is carried out very urgently or is an emergency [8], and it is recognized that this process is the choice of the prospective mother for giving birth [9].

However, in a cesarean procedure, a decision must be made by doctor or medical personnel because there are many things that must be considered, especially the prospective mother's medical record data, with that only being seen whether a cesarean is performed or not. but predictions require strong and accurate analysis to reduce errors in making decisions. For this reason, a method is needed so that doctors or medical personnel can assist in the decision to have a cesarean section.

One of the solutions offered in cesarean prediction is ML method because it is very suitable and accurate in making decisions and analyzing very large data sets based on Unsupervised and Supervised data, especially in the field of medicine, especially in caesarean births [10] [11]. One of the advantages of ML is that it can display visualization or interpretability to be able to solve problems in predictions and decision making by looking at highly influential features [12] with the proposed method being able to reduce errors in caesarean section. However, it is acknowledged that ML also has limitations in the amount of data, data processing, model difficulties that are in accordance with the predicted results and especially the predicted results but are difficult to translate in decision making or are called Black Boxes [13][14].

The contribution of this study is to provide suggestions in the comparison of ML interpretable prediction models with Feature Importance, SHAP, and LIME whose results are considered the easiest to understand and show the results of which features are the most dominant or influential which are used as guidelines for decision making for obstetricians or medical personnel.

The use of these three models in general is because they are very popular in interpretable ML and can identify features that are very important and influential in predicting the results of the issued model, especially easy to understand in visual form. With this output, you can make the right decisions in making applications or prediction systems that will be used later.

LITERATURE REVIEW

It is admitted that there are not many studies related to the feature importance model, SHAP, and LIME, but these models can be used as a guide to be used as a solution in predicting cesarean.

A. Building Prediction Model by using Feature Importance

Valko and Hauskrecht [15] in this study how to understand the characteristics and features of medical record data which greatly influence the doctor's decision to prescribe drugs to patients. The data used by postoperative heart patients totaled 4486 data and the results were well obtained the highest feature in the prediction was the lab results in prescribing drugs.

Sheila A. Magboo and Peter C. Magboo [16] this study discuss clinical workflows that create problems in making decisions for patients, therefore a system that is integrated is created from the initial patient registration to obtaining the final decision from the doctor and finally getting predictions the patient. The models used are Random Forest (RF), AdaBoost, and K-Nearest Neighbors (K-NN) then LIME to visualize the features which finally look for the most influential Importance features.

Gabrieli et al [17] apply feature importance to create a framework model in designing a cross-sensitive sensor array to speed up water testing is expected to be able to monitor water quality.

Chu et al [18] in this study applied the technique to weather data and studied which weather features affect traffic the most, expected to introduce convolutional embedding to convert data with information into spatial images suitable for convolutional neural networks.

Xian-Li [19] This study proposes a framework that focuses on the study of feature importance, which is embedded into a representative learning algorithm. The experimental results show that it significantly improves the learning performance of the embedded algorithm, and the study of feature importance has the potential to play an important role in transfer learning.

Huda et al [20] in a study on the prediction of Diabetic Retinopathy eye disease which causes damage to the retina of the eye by using the Decision Tree, Logistic Regression model to look for accuracy and precision, finally with feature importance by looking for which feature is highest and the influence of the eye disease.

B. Building Prediction Model by using SHAP.

Chat et al [21] research suicide and look at the importance of each feature shown. The experiment shows that the model with SHAP can interpret and understand the predictive nature of individuals with suicide attempts and intentions.

Zhao et al [22] in their discussion of feature selection with SHAP used the Parkinson's disease dataset by combining four classifications namely Deep Forest (GCForest), Extreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM) and Random Forest (RF). The results obtained by the SHAP feature selection method have excellent performance in the diagnosis of Parkinson's disease and provide a reference for doctors in the diagnosis and prevention of Parkinson's disease.

Hu et al [23] research the relationship between heavy metal exposure and coronary heart disease by using the SHAP model to interpret the features to visualize the decision-making capacity of the selected model.

Ullah et al [24] research on the growth of electric cars which infrastructure is very limited, the model used is a combination with XGBoost to get the highest accuracy from the dataset used and SHAP to see attributes that influence features and complex nonlinear and interactive effects of various behaviors charging station selection.

Lin and Gao [25] discussed looking at the criteria in evaluating the contribution of the marginal field of each feature used to predict results and evaluating the company's resilience to profitability, liquidity, and so on.

C. Building Prediction Model by using LIME.

Cho et al [26] in a study discussing predicting the disposition of post-stroke hospital discharge with a machine learning model in improving predictions by explaining with the LIME interpretation method.

Bodini et al [27] in this discussion about ST-Elevation Myocardial Infarction (STEMI) can be detected on an electrocardiogram (ECG) using the ML algorithm but does not provide sufficient interpretability analysis, therefore LIME is needed to highlight which part contributes most to the detection.

Chen et al [28] in this paper on the detection of malignant tumors in women, with the Mammography Interpretable Diagnosis Model (MIDM) model which is based on the construction of a medical text semantic tree to achieve structure than with the LIME model to see the predictive features for comparison of these models.

Stieler et al [29] in this study discussed creating a system for skin image analysis by applying the LIME model from a dermatologist's diagnostic approach.

Kamal et al [30] in this study on the prediction of Alzheimer's patients by image processing detection. The model is used with CNN, KNN, SVC, and XGBoost to compare accuracy results, then LIME to interpret which feature has the most influence in the prediction of Alzheimer's.

Proposed Model

The proposed model is a cesarean prediction by looking at the very dominant and influential features of the model given, which one is the best in terms of visual form and accuracy, testing this model with the Python programming language with the Jupyter Notebook Application.

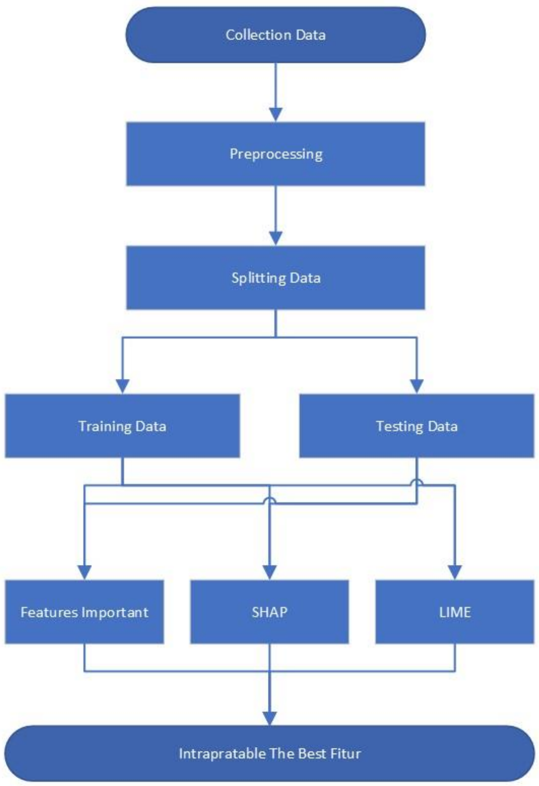

FIGURE 1. Caesar Prediction Model

A. *Collection Data*

The model was built using a dataset downloaded from secondary data https://datadryad.org/stash/dataset/doi:10.5061/dryad.g7t04 which consists of 31 features and two prediction classes divided into cesarean (1) and not cesarean (0).

TABLE I
ATRIBUTES, DESCRIPTION AND VALUE DATA SET

Attributes	Place of Text	Value
Age.	Year of patience.	Number
Duration.	Next day to next pregnancy.	Number
Obesity.	Weight.	0 or 1
Ruptured.	Premature rupture of membranes.	0 or 1
Placenta.	Complicated disorders in which part or all the placenta separates from the uterine wall before the baby is born.	0 or 1
Condition placenta.	Condition of the placenta.	0 or 1
Premature	A condition in which the placenta separates from the uterine lining.	0 or 1
Bleeding.	The loss of blood.	0 or 1
Fake Childbirth.	Sporadic uterine contractions.	0 or 1
Pregnancy Over	Pregnancy Over 40 Weeks.	0 or 1
Premature Labor.	Deliveries that occurred before 37 weeks of gestation. Fetuses born usually have less weight.	0 or 1
Contractions.	Primary contractions are not strong.	0 or 1
Medical diagnosis.	Describe the presence of labor abnormalities in the 1st stage.	0 or 1
Perineal laceration.	Damage to the female genital organs that usually occurs during childbirth.	0 or 1
Obstetric trauma.	Fear after childbirth.	0 or 1
Postpartum haemorrhage.	Bleeding from the birth canal immediately after delivery.	0 or 1
Placenta without bleeding.	A condition when the placenta or placenta does not come out on its own or is stuck in the uterus after delivery.	0 or 1
Anesthesia.	Effects after anesthesia.	0 or 1
Complications.	Childbirth complications	0 or 1
Genital and pelvic.	Infection of the female reproductive organs.	0 or 1
Single birth.	First childbirth with vacuum extractor.	0 or 1
Meets fault.	Mistakes diagnosis.	0 or 1
Chronic postrheumatic.	The disease is chronic and occurs for life and usually affects both men and women.	0 or 1
Pre-existing essential.	Hypertension that is not caused by certain conditions, diseases, or drugs but pregnancy.	0 or 1
Posttraumatic.	The tube that carries urine from the bladder out of the body.	0 or 1
Anterior dislocation.	A condition in which the bony hump of the upper arm detaches from the shoulder joint.	0 or 1
Acute suppurative	Inflammation of the middle ear is a condition that occurs when a virus or bacteria causes the area behind the eardrum to become inflamed.	0 or 1 0 or 1
Eye vision.	Evaluate your vision condition and check for eye diseases.	0 or 1
Goose neck.	A disorder that makes the shape of the fingers look like the neck of a swan.	0 or 1
Twin pregnancy.	Identical twins who share both a placenta and an amniotic sac.	0 or 1
Latex allergy	The immune system's reaction to the proteins in natural rubber latex, a product made from the liquid of the rubber tree.	0 or 1

B. Preprocessing

The first step in building a model, especially in prediction, is preprocessing the data so that it can be seen which data is noisy or incomplete, because if there are gaps in the data, it will cause the model to be wrong and the results to be less quality. In testing, in Table. II. below there is no noise or empty data.

TABLE II
LOOKING FOR EMPTY OR NOISY DATA

Attributes	Value
Age.	NUMBER
Duration.	NUMBER
Obesity.	0 OR 1
Ruptured.	0 OR 1
Placenta.	0 OR 1
Condition placenta.	0 OR 1
Premature	0 OR 1
Bleeding.	0 OR 1
Fake Childbirth.	0 OR 1
Pregnancy Over	0 OR 1
Premature Labor.	0 OR 1
Contractions.	0 OR 1
Medical diagnosis.	0 OR 1
Perineal laceration.	0 OR 1
Obstetric trauma.	0 OR 1
Postpartum haemorrhage.	0 OR 1
Placenta without bleeding.	0 OR 1
Anesthesia.	0 OR 1
Complications.	0 OR 1
Genital and pelvic.	0 OR 1
Single birth.	0 OR 1
Meets fault.	0 OR 1
Chronic postrheumatic.	0 OR 1
Pre-existing essential.	0 OR 1
Posttraumatic.	0 OR 1
Anterior dislocation.	0 OR 1
Acute suppurative	0 OR 1
Eye vision.	0 OR 1
Goose neck.	0 OR 1
Twin pregnancy.	0 OR 1
Latex allergy	0 OR 1

C. Splitting Data

The next step is data sharing for 70% training which is useful for displaying the results of the model and whether it is feasible to use and 30% testing which is useful for seeing the performance of the model used.

D. Interprability Model

There are several techniques in interpretability in simple ML with Scatter Plots, Box Plots, Correlation Matrics, Decision Trees, and Logistic Regression. There are also other techniques with updates from other models, namely CNN, RNN, and DNN [31]. However, in this study using Feature Important, SHAP, and LIME, because one is used in the health sector [32], these models are very easy to understand and apply, are very suitable for simple ones, and can be used with other models.

RESULT

Figure 2 The Feature Important model shows 32 features in Caesar's prediction which show the highest to the lowest feature contribution values in the prediction results with different colors. The contribution value of the 32 input features as a whole and each bar in the summary plot shows the contribution value of each input feature to the overall prediction results. The longer the value, the more influential the value. There are 4 very high and important features, namely Meet Fault, Genital and Pelvic, Duration, and Age.

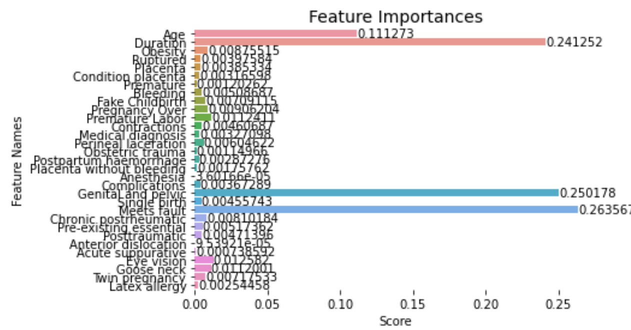

FIGURE 2. Feature Important Interprability

In Figure 3 using the SHAP Plot Bar model. Shows the order in which features influence the prediction results of the classification model (Caesar or Non-Caesar). The higher the contribution value of an input feature, the longer the displayed bar. The highest results were Meet Fault and Genital and Pelvic.

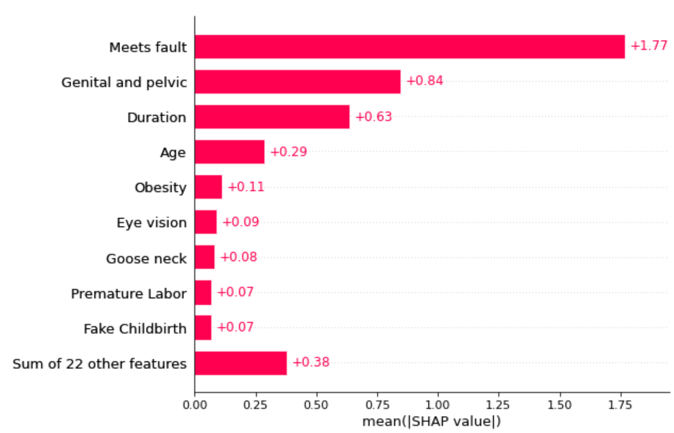

FIGURE 3. SHAP Plot Bar Interprability

Figure 4 after the plot summary image on SHAP will show that the two data features that have the most influence on the prediction results of the model are: Meet Fault, Genital, and Pelvic. The higher the value of the Meet Fault feature, the higher the effect on the prediction results of the model. Conversely, the lower the value of the Meet Fault feature, the lower the influence on the prediction results of the model. The higher the value of the Genital and Pelvic features, the lower the effect on the prediction results of the model. Conversely, the lower the value of the Genital and Pelvic features, the higher the influence on the prediction results of the model, and the effects of the Duration and Age features are not linear.

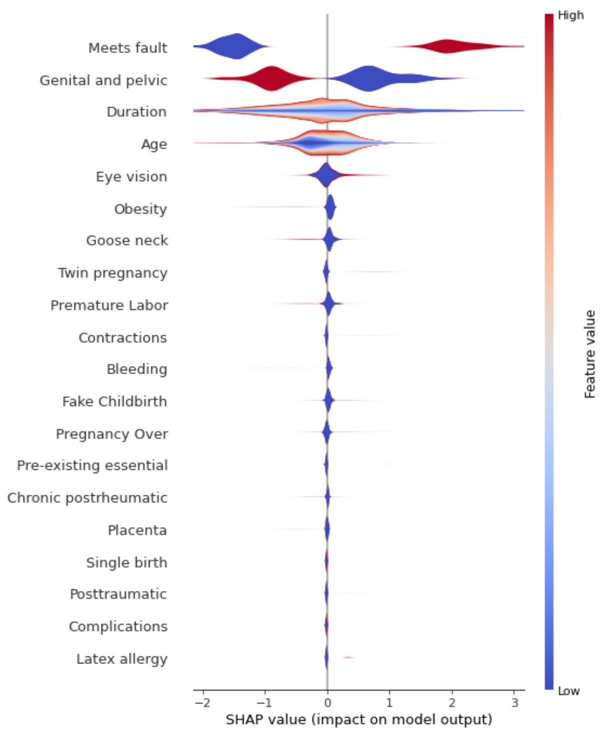

FIGURE 4. SHAP Summary Interprability

Figure 5 the results on LIME will show that the left graph shows that the prediction of Caesar probability is 86% while 14% is Not Caesar. The middle graph shows the highest and most influential feature score in Caesar's prediction, namely Meet Fault, Genital and Pelvic, Anterior dislocation, Pre-existing essential, and Single birth. On the other hand, Caesar's predictions are Bleeding, Obesity, and Age. The graph on the right shows the top five features and their respective values. Features highlighted in blue contribute to class 1 (cesarean) while features highlighted in orange contribute to class 0 (Not cesarean).

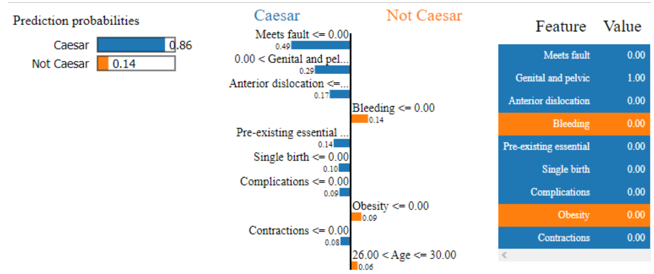

FIGURE 5. LIME Interprability

Conclusion And Future Work

From a comparison of Important Features, SHAP and LIME can provide an explicit explanation of the results of Caesarean predictions and allow doctors to see and make decisions on features that are very influential and can understand expectant mothers during a Caesarean section. If you look at the models that are easy to understand, namely Feature Important and SHAP in the form of Plot Bars, however, the three models still produce 2 very influential features, namely Meet Fault and Genital and Pelvic.

It is acknowledged that there is a deficiency with the interpretability model, one of which is using this model, one of which is using certain models such as Feature Important with Random Forest Classifier, if using other models then the results are not necessarily the same as the features. It also depends on the data sample, if there is a large amount of data and the attribute values also change, the interpretation results will also change.

However, for further research, you can use other Interprability models such as Partial Dependence Plots, Anchors, Global Surrogate Models, and others to be able to compare which one is closer to the prediction so that it can assist doctors in making decisions about Caesarean section.

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