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Enhancing Maternal Outcome Prediction Using Explainable Artificial Intelligence for Women of Childbearing Age

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***Abstract* - Our research has identified a significant shift in the utilization of machine learning models for prediction and decision-making. Rather than solely relying on these models, there is now a growing focus on their explainability and interpretability. Data for this study were acquired between 2019 and 2022 in the Nigerian Coastal Plain, encompassing information from two thousand patients collected at secondary and tertiary healthcare centers, comprising fifteen distinct features. Our team utilized the Shapley additive explanation (SHAP) method to achieve this goal, adhering to the principle of fair play from game theory, giving every maternal attribute used in our work equal consideration. With an RF model and explainable AI techniques, we aimed to predict maternal outcomes and provide comprehensive insights into the most important features of mothers within the bearing age group. We summarized the study's findings in terms of demography, laboratory results, physical examination, and mode of delivery. Our analysis revealed that mothers of an older age are more likely to experience a caesarean section or have a child with Down syndrome. However, we also found that the SHAP method, along with other XAI methods such as LIME and CIU, can play a vital role in improving satisfaction, time, and understanding. This approach can greatly improve medical decision-making, benefiting both mothers and their children. Our confidence in these findings is high, and we believe they will have a noteworthy impact on the field of parental health.**
***Keywords:* Shapley Additive Attribution, ML, Interpretability, Feature Relevance, Maternal Outcome**

I. INTRODUCTION

Maternal health care delivery is one of the most demanding areas in the health facilities, requiring huge attention from physicians and non- physicians to reduce complications or emergency situations that might occur, during and after deliveries. Such situation include Urinary Tract Infections (UTIs) [1], Anaemia [2], mental health conditions [3], Hypertension [4], Gestational diabetes [5], [6], Obesity and weight gain [7], Intense queasiness and vomiting during pregnancy [8] and Infections with HIV [9], [10], viral hepatitis [11], [12], STDs [9], and TB [13], [14], these presentations can result to morbidity or mortality among mothers within the posture age. Although, there are significant efforts by private and public organizations to reduce mortality ratio, the United Nations Internationals Children Emergency (UNICEF) [15], [16] gave a report that there substantial reduction of 39 per cent of maternal mortality. Presently, this is a clear evidence that there are efforts in place to ensure that mothers within bearing age may not experience complications during and after pregnancy.

However, scholars are of the view that more awareness should be tailored towards improving on maternal outcome, to a large extent, in order to reduce human errors or poor clinical and physical examinations, in cases where medical or non-medical personnel may not be able to ascertain exactly what went wrong with the patient, so as to address the issue with right method Poor attention to medical situations is bound to occur because of the delay in deciding to seek proper therapeutic attention for an obstetric emergency, getting to the right maternity facility, also obtaining enough treatment once there. In this light, computational systems are seen as useful tools to complement the effort of medical practitioners in predicting and diagnosing medical problems.

The increasing need for employing Machine Learning Classifier (MLC) to improve maternal health has become inevitable. Hence, researchers keep deploying the use of automated processing techniques, in the assessment and diagnosis of patient's maternal outcomes. Some studies addressing the subject matter include,

1. The use of neural network-based learning to envisage gestation outcomes in repeated reproductive failure patients, the work connotes that combining data panels had no significant impact on predicting pregnancy outcomes, also other factors play a more important role.

2. However, their work gave a new insight into the importance of procreative immunology and also establishes the basis for supporting physicians to plan more detailed and customized diagnoses and provide better management for individuals with recurrent reproductive failure [17].
3. Machine learning-based methods was used to predict late-onset preeclampsia, and suggested that more studies should be encouraged to improve on clinical diagnosis [18].
4. Suggested model for effective management of obstetric risks using predictive decision support such as Random forest classifier because it enhances prediction performance through statistical methods validates the efficiency of knowledge in classifying and managing women with the bearing age [19].
5. Predict the risk of common maternal post-delivery complications, with the help of machine learning algorithm [20].
6. Used predictive analytics for real-time data analysis can improve the accuracy of predicting successful vaginal deliveries compared to traditional methods. This advancement could be advantageous for expectant mothers. Their developed models have successfully translated and enumerated the collected data in the labour unit, resulting in a highly reliable medical instrument that provides an individualized risk score. With this tool, unnecessary interventions can be confidently avoided [21].
7. Applying a machine learning algorithm to allocate a personalized risk score for successful vaginal birth after a surgical birth could assist in decision-making and potentially contribute to lowering caesarean delivery rates [22].
8. Predict the feeling of safety that healthcare workers will experience at work during the initial stages of the COVID-19 virus for mothers and neonates [23]. The majority of the results obtained are basically in a black box because it only gives a holistic view of the performance of the model, not throwing more light on strength of input features used to predict the model, which may pose some level of bias. Based on this reason, an effort to explore Explainable Artificial Intelligence (XAI) becomes necessary.

XAI helps to describe an AI model, showcase the potential biases and expected impact, build trust on the model used, increase confident level of the input variable, characterize model accuracy, fairness and transparency, reduce the impact of model bias and reduce unintended outcomes when putting AI models into assembly. There are four basic XAI algorithms which are Local Interpretable Model-agnostic Explanations (LIME) [24], it estimates the forecast locally thereby converting the input around the class of curiosity until it arrives at a linear equivalence. The SHapley Additive exPlanations (SHAP) [25] helps to describe the outcome fairly among the features, though, it basically depend on how each function contributes in terms of local and global interpretability. The Counterfactuals/Adversarial attacks [26], [27] also called Contextual Importance and Utility (CIU), it gives a true picture on how the data looks like, because a feature might be important in one context but may not be inappropriate in another. Lastly is the layerwise relevance propagation (LRP) which helps to further explain the context input features most specially predicting an image**.** It is in this vein that some scholars are engaged in the use of XAI to address maternal predictions, Bosschieter *et al.,* [28] applied interpretable ML to predict parental and fetal outcomes, XAI method reveal a surprising insights into the features contributing to risk associated with the prediction of maternal and fetal outcomes, in their study Explainable Boosting Machine (EBM) result matches with the accuracy of the black-box model.

Wesołowski *et al.,* [29] adopted an understandable artificial intelligence approach for envisaging cardiovascular outcomes using Electronic Health Records (EHR), which can be transformed into an enormous collections of data into compact, portable machines for results[30]. Marvin and Alam [31] used explainable feature learning for predicting Neonatal Intensive Care Unit (NICU) admissions indicated that a proactive extrapolative technological method can enhance the achievement of neonatal and maternal monitoring as well as treatment plans. There is no doubt XAI seeks to be an appropriate tools to enhance maternal outcomes. However, objectives of this work are as follows: examining machine learning tools to predict maternal outcome, using RF model with transparent AI techniques in more clear and insightful means for predicting maternal outcomes, as well as to derive and systematically demonstrate the most significant features among mothers within the bearing age to improve medical verdict.

The rest of the paper is organized as follows: Section II showcase the related works on existing XAI for predicting maternal outcome. Sections III will comprise the presentation of Materials and Methods, whereas Section IV presents the Results and Discussion, while Section V is the Conclusion.

II. REVIEW OF LITERATURE

Machine learning models are not out of date and they can be considered reliable, although the effectiveness of the models that are generated is limited because the machines may not be able to completely explain their verdicts and actions to humans/users. Therefore, transparent and interpretable machine learning algorithms are becoming increasingly popular as they increase trust by allowing people to understand how they work. Currently, some studies are primarily welcoming the use of XAI approaches both in medical and non-medical domain.

Notably, Knapič *et al.,* [32] explored XAI for individual guidance framework in the medical domain, Pawar *et al.,* [33] explored the use of XAI in health care, also Khedkar *et al.,* [34] used Explainable AI in Healthcare, Holzinger et al. [35] conducted a work to explain why XAI systems will be useful in medicine. Another work by Cinà *et al.,* [36] gave the reason why we need Explainable AI for Healthcare, Holzinger [37] combined XAI and Multi-Modal Causality in medicine, Papanastasopoulos *et al.,* [38] used XAI for medical imaging basically they considered deep learning ensemble of convolutional neural networks (CNN) for categorizing estrogen receptor status using breast magnetic resonance scans. Folke, *et al.,* [39] used Bayesian to explain pneumothorax diagnoses with explainable AI in medical imaging.

Muddamsetty *et al.,* [38], [40], [41] assessed expert in medical domain, this was achieved using XAI, Meacham *et al.,* [42] develop explainable machining learning predictions for patient remittance medical application. Schoonderwoerd, *et al.,* [43] developed a design pattern for explanations of clinical decision support system using XAI. Anguita-Ruiz, *et al.,* [44] employed transparent AI for the empathy of organically pertinent gene expression designs in longitudinal human studies and acumens from obesity research.

Jiménez-Luna, *et al.,* [45] investigated drug discovery with explainable artificial intelligence, they encouraged additional efforts by researchers to accept and adopt the prominent algorithmic concepts of interpretable machine intelligence. This in turn will help to improve the decisions of the physicians and to a large extent reduce various failure cases [46] among health care givers.

Ahmed, *et al.,* [47] stressed the importance of XAI, in assisting the medical care givers to understand the counter check and logic decisions before implementing on the patient for a better cause. In the work Dauda, *et al.,* [48] supported that the adaptation of clear models in healthcare will substantially improve users' trust in AI algorithms in healthcare systems. Subsequently, several survey have been tailored towards XAI, among which are [49]-[57]. Their summary was that XAI provides meaningful insight on quantifying explainability and facilitates a human-friendly explanation for decision making.

Our work is taken a leaf from the previous works titled analytic model for intelligent management of predictive decision support in obstetric risks [19] and evaluations of classifier optimality in single and multi-labeled classification problems related to obstetric outcomes [58], where several model, were tested, but the best of it all is random forest. Tree bagging exemplary, algorithm provides a higher level of accuracy in predicting outcomes.

RF has been utilized in various aspects of medical domain to improve on decision making towards maternal outcome such as Macrosomia [59], stillbirth [60], mortality [61], miscarriage [62], Pre-term [63], Placentae Previa [64], UTI [65], Stillbrith [66]. The outcomes, despite their technical nature, can be challenging for individuals not well-versed in computer science to decipher due to their somewhat opaque nature. It is against this backdrop, our work sought to explore XAI our previous maternal dataset to improve medical decisions.

III. MATERIALS AND PROCEDURES

A. Data Acquisition

Data for this study was obtained from Niger Delta region of Nigeria between 2019 and 2022. Two thousand patients' data were collected from secondary and tertiary health care centres. Ethical approval was sought and obtained from respectively from the health facilities we used for this study. Fifteen (15) features were considered for the prediction of maternal outcome, which were Maternal Blood Pressure (MBPM), Maternal Weight (MW), Hemoglobin Level (HL), Pack Cell Volume Level (PCVL), Mode of Delivery (MOD), Pulse Rate (PR), Malaria Frequency (MF), Hepatitis B (HB), Respiratory Disorder (RD), Diabetes Status (DS), Herbal Ingestion (HI), Age (A), Ascorbic Acid Level (ACC), Antenatal Booking, (AB)Preeclampsia (PREE), and Maternal Delivery Outcome (MDO).

B. Generalized Linear Model

The generalized linear model (GLM) serves as an elastic iteration of ordinary linear regression, extensively applied in medical studies. It facilitates the interpretation of the impact of descriptive variable x_i for outcome y using a coefficient. Also, for logistic regression model, the log-odds of the probability p is a weighted sum of the instructive variables, $x_i \in X_i$ and a_i, and expressed as follows.

$$\log\frac{p}{1-p} = b + \sum_{i=1}^{k} a_i x_i \qquad (1)$$

b represents a constant term and k is the number of features. Increasing x_i by 1, results in a corresponding increase in the logit increase by a_i. If $a_i > 0$, a largerx_i has a positive impact on the outcome, while a negative a_i means a negative impact of a larger x_i. However, if all attributes are unvarying, i.e., ∀i, E(x_i) = 0 and Var(x_i) = 1, the estimated coefficients are called standardized parameters or beta factor. The beta β_i is a dimensionless quantity. Consequently, we can directly compare beta coefficients. The significant feature is evaluated by the absolute value of the beta coefficient. A value with lager mean is of great importance. Thus, connote that when features are standardized, the connection between features and GLM outcome becomes clear, rendering the model easily interpretable. Nevertheless, building precise prediction models involving interactions and non-linear terms using the generalized linear model can prove challenging in certain scenarios.

C. Tree-based Decision Method and Ensemble Tree Techniques

The tree model is one of the taxonomy algorithms that involve dividing data into subclasses using easy-to-

understand if-then rules. However, creating an accurate model with just one decision tree can be difficult.
Ensemble tree method is reliable for higher accuracy; also, it combines multiple decision trees for more robust predictions. Ensemble model helps to improve weak model/learner to perform stronger model/learner. Other include Gradient Boosting Decision Tree (GBDT) and Random Forest which are good examples of ensemble tree models. The strength of the model its ability of combining decision trees for better predictions, especially in cases of features in high dimensions and relationships that are non-linear.

However, the ensemble method is frequently employed in machine learning. The usage of numerous decision trees can produce strong estimate performance, but it may be challenging to understand the model's conditional statements.

D. SHapley Additive exPlanations (SHAP) Method

In this work we will adopt the SHAP method, because the strength of Shapley value based explanations of machine learning models is drawn from the cooperative game theory to allocate credit for a model's output $\varphi_i(f, x)$. According to Lundberg and lee [67] the SHAP AI context is established by linking the outputs of ML models to optimal credit allocations through local explanations using Shapley values from game theory and their relevant extensions. [68]. Thus, the Shapley values, derived by determining the average marginal contribution of a feature value over all possible combinations, serve as integrated measures of attribute importance and significance.

$$\varphi_i(f, x) = \sum_{Z^1 \subseteq X^1} \frac{|Z^1|!\,(M - |Z^1| - 1)}{M!} [f_x(Z^1) - f_x(Z^1)!] \qquad (2)$$

However, the model can assess an existing model by incorporating only a subset of features, effectively integrating out the other aspects through a conditional expected value formulation. This approach considers the marginal impact of the specific feature.$[f_x(Z^1) - f_x(Z^1)!]$ is used to calculate all the subsets Z to get the Shapley value for a element i, such that model estimates of all subsets with and without the facet are computed and added to get the Shapley value for that inputs to make the Additive exPlanations. The preservative explanations or the Shapley value should satisfy four properties: linearity, productivity, symmetry and null player. By using the idea of the Shapley value, Shapley Additive exPlanation (SHAP) represents the outcome of patient i: $f_x(Z^i)$ as the sum of each peculiarity - j's influence $\varphi_i(z_j^i)$.

$$\varphi_0 = \frac{1}{N} \sum_{I=1}^{N} f(z_j^i) \qquad (3)$$

$$\varphi_i(z_j^i) = \varphi_i(z_j^i) - \frac{1}{N} \sum_{v=1}^{N} f(z_j^v) \qquad (4)$$

$$f(x^i) = \varphi_0 + \frac{1}{N} \sum_{I=1}^{N} f(z_j^i) \qquad (5)$$

N represents the total count of patients. We derived ∀i, E(φ_i (Xi)) = $\frac{1}{N} \sum_{I=1}^{N} f(z_j^i)$ *from Equation* 5

The SHAP value has been recognized to be stable [67]. It could also be applicable to GLM and all other machine learning techniques. With the amount of features, naïve SHAP calculations take exponentially longer to complete. j; however, Lundberg *et al.,* proposed efficient time algorithm for decision and ensemble trees model [69]. This procedure is combined major collaborative tree bases among other such as Random Forest.

However, there is a strong relationship between the feature x_j and SHAP value in GLM is given as

$$\varphi_{GLM}(z_j^i) = a_j x_j^1 - E(a_j X_j) = a_j x_j^1 - a_j E(X_j) \qquad (6)$$

Where x_j has a proportional relation with its SHAP value and the commensurate factor is given by a_j. Therefore, the result is consistent with existing understandings of GLM.

E. Proposed SHAP Model for Maternal Outcome

Explainability remains a focal point for machine algorithm (ML) because it helps to explain complexity of ML model. To achieve this, the ante-hoc and post-hoc draws a shift from the black box to the white box, for easy understanding, where we can access the gradient or weight of independent variables. To this end, we aimed at using the proposed SHAP model by first testing our maternal dataset using Random Forest Regressor model for prediction, then past it into the SHAP algorithm to arrive at an interpretable model over the predictive model.

The model in Figure 1 in summed up into three levels. The first level is derived from the doctor during antenatal visit, at that stage the patient demography status is drawn, the physician does a physical examination on the patient to ensure that the patient is in good condition, otherwise the patient may be asked to undergo some laboratory test which will be taking him back to the physician. Sometimes previous maternal outcome made be required. The second level is to pre-process the features collected into an understanding ML format, to enable the ML model to produce a predictive model. The third level is to employ the explainable and interpretable model. One hallmark of our model is that it helps to save time, the physician quickly looks at it, understands what feature to look out for in a patient within the bearing age during presentation, it also enhance the computational prediction, thereby gives room for modification at each time to increase the computational stability in terms of prediction.

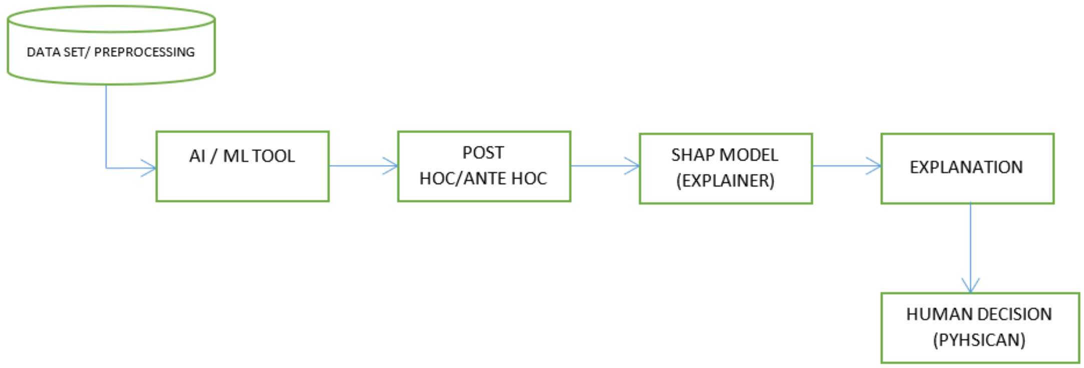

Fig. 1 Proposed SHAP model for explainable maternal outcome

IV. RESULTS AND DISCUSSION

Most of the plots display the model output's estimated magnitude, where each row illustrates the positive (red) or negative (blue) constitute of each feature. We use waterfall, beeswarm, heat map, and SHAP value (impact on model output). The cluster plot was also used to illustrate explanations for individual maternal outcomes, which helped explain the relationship amid features and the outcome for a sole row of objects as inputs. Subsequently, Figure 2 and Figure 3 illustrate bar plots for predicting maternal outcomes. Meanwhile, Figure 4, Figure 5, and Figure 6 depict beeswarm plots aimed at maternal outcome prediction. Figures 7 and 8 showcase cluster plots designed to predict maternal outcomes, while Figures 9, 10, and 11 present heat map plots with the same objective. Additionally, Figure 12 exhibits a scatter plot for maternal outcome prediction, and Figure 13 featuresa Waterfall plot with a similar focus.

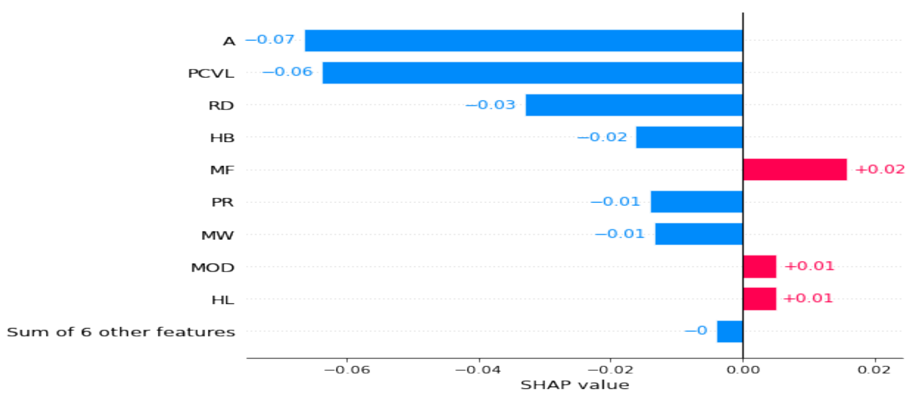

Fig. 2 Plot Bar to Predict Maternal Outcome

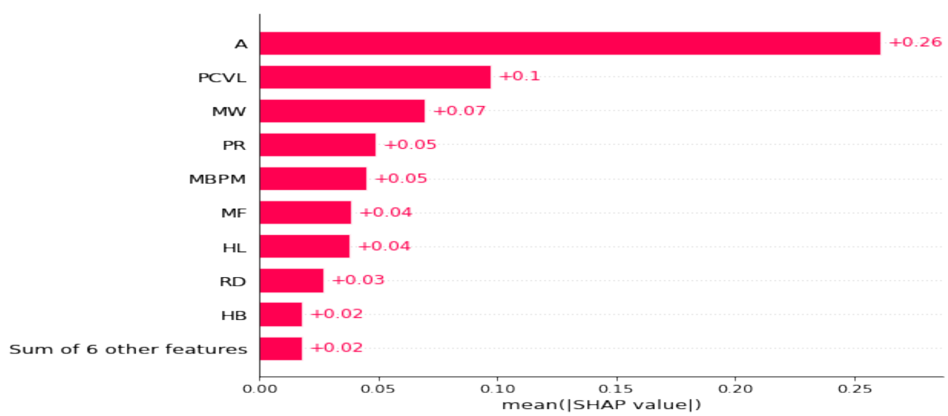

Fig. 3 Plot Bar to Predict Maternal Outcome

A. The Beeswarm Plot

Figure 4-5 clearly shows that the beeswarm plot effectively illustrates how each variable expression of an individual affects the ML model's prediction towards a maternal outcome. The Positive SHAP values clearly indicate a definite shift in the expected model prediction towards a maternal outcome.

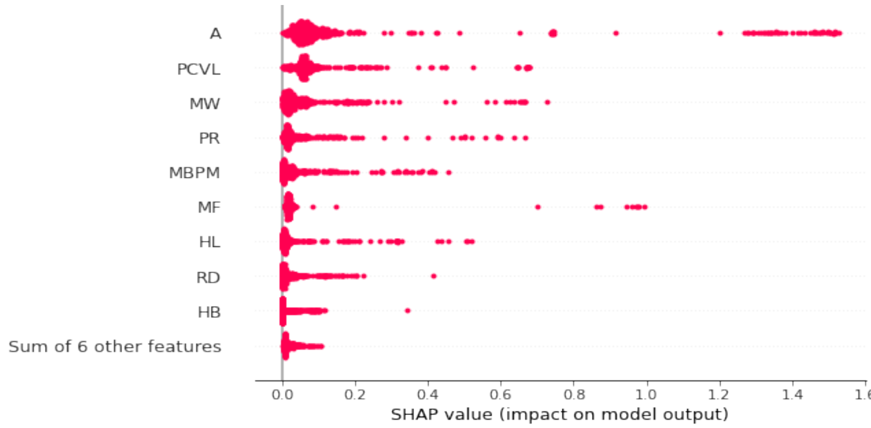

Fig. 4 Beeswarmplot to Predict Maternal Outcome

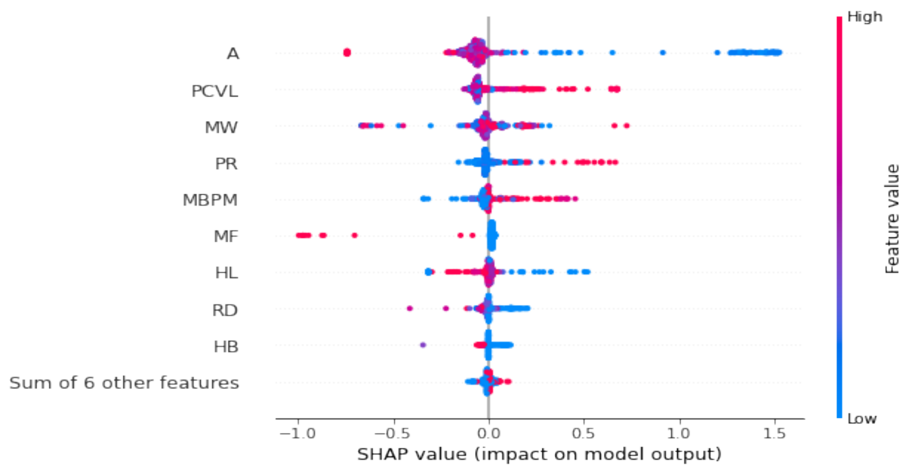

Fig. 5 Beeswarm Plot to Predict Maternal Outcome

Furthermore, Figure 4-5 also indicates that the Beeswarm plot of SHAP helps to give the best calculation for the nine highest ranking variables. In this study, individual dots are used to represent people, ranked by their level of importance. The positive SHAP values indicate how variations in the expression of the variables influence the model's prediction for maternal outcome. However, the beeswarm graphic demonstrates how each person's unique variable expressions influence the ML model's prediction of the maternal outcome.

Figure 6 illustrate the strength of all the input features, in predicting maternal outcome of patients within the bearing age.

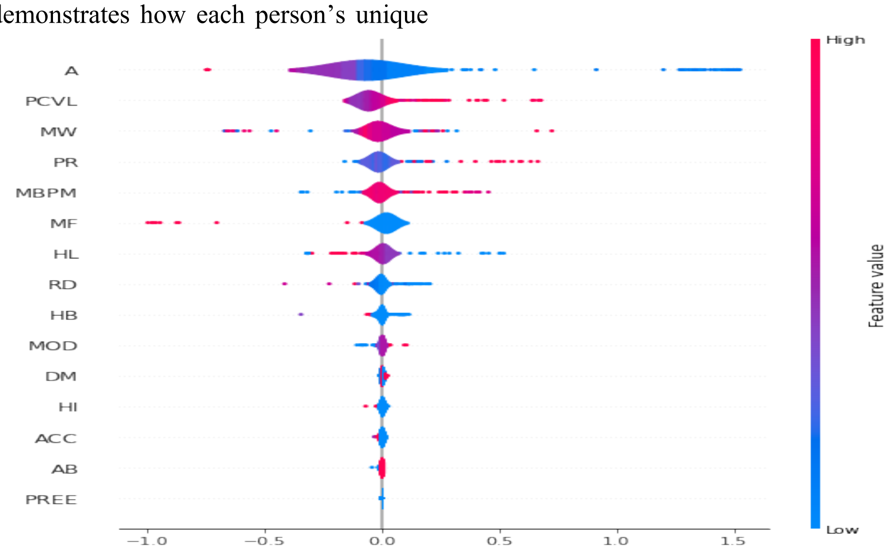

Fig. 6 Beeswarm Plot to Predict Maternal Outcome

Positive SHAP values represent a shift in the predicted maternal outcome of the model. The graphic is based on the ML model with leave-one-site-out cross-validation and all factors considered.

B. Cluster Plot

SHAP values provide valuable insights into the clustering model's predictions for maternal outcomes. They enhance interpretability, enable personalized interventions, validate the model, and help identify potential biases, ultimately supporting healthcare providers in making informed decisions to improve maternal health and well-being (Figure 7).

The goal here is to cluster those maternal values that could aid physicians in improving their decision-making in an emergency.

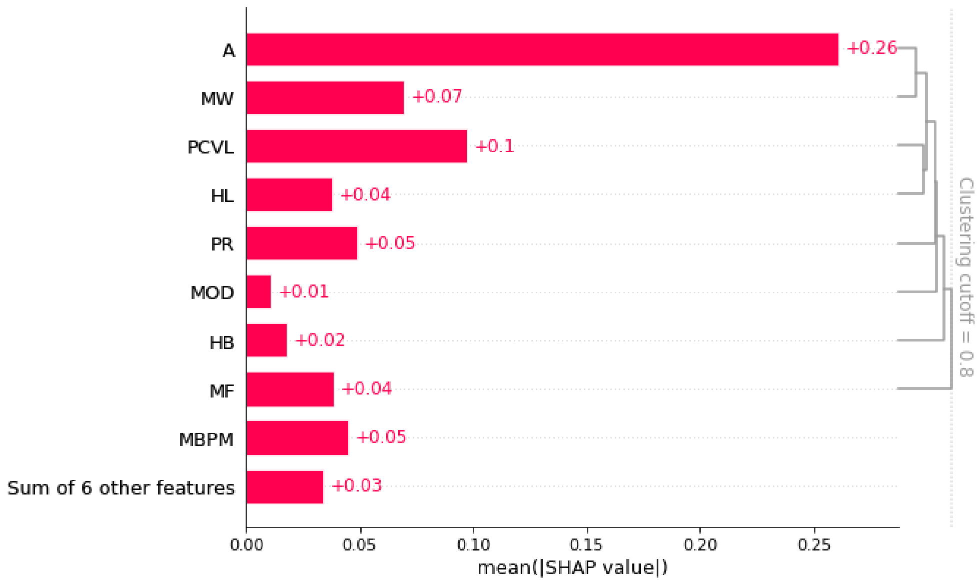

Fig. 7 Cluster Plot to Predict Maternal Outcome

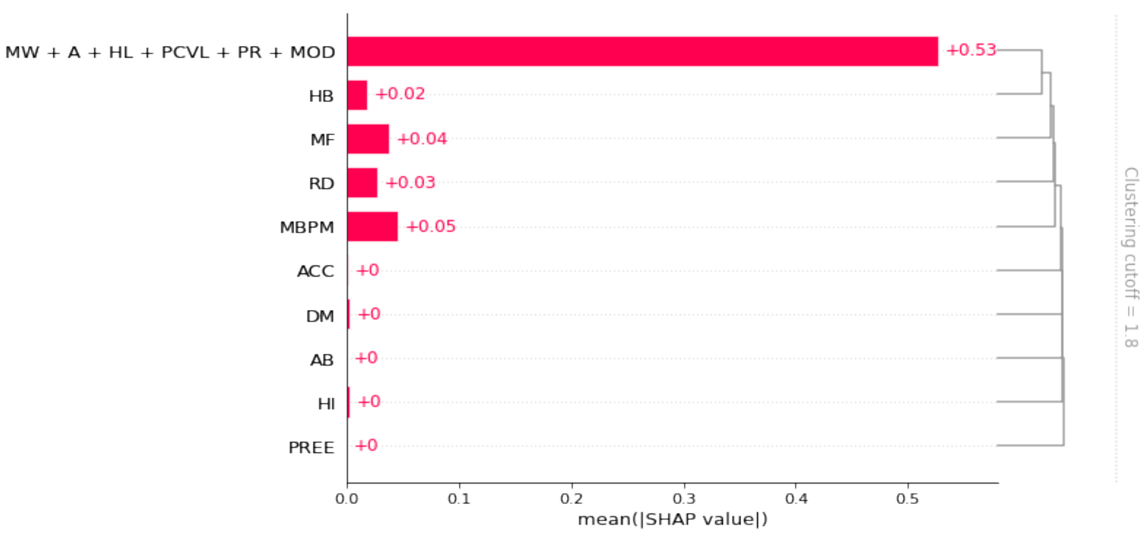

Fig. 8 Cluster Plot to Predict Maternal Outcome

The cluster above helps to show the strength of the basic antenatal procedure that mothers within bearing age undergo, to ensure a successful maternal outcome. Each of these features are very important. The first clustered features are MW, A, HL, PCVL, PR and MOD followed by MBPM, then MF and RD, the last is HB (Figure 9, 10, 11 and 12).

C. The Heat Map

Heat Map Plot to Predict Maternal Outcome are shown as follows.

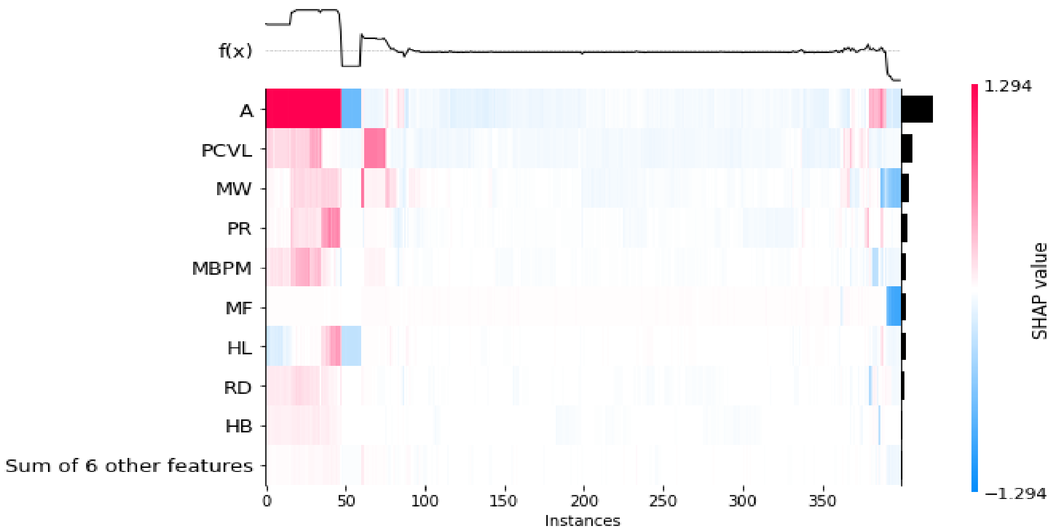

Fig. 9 Heat Map Plot to Predict Maternal Outcome

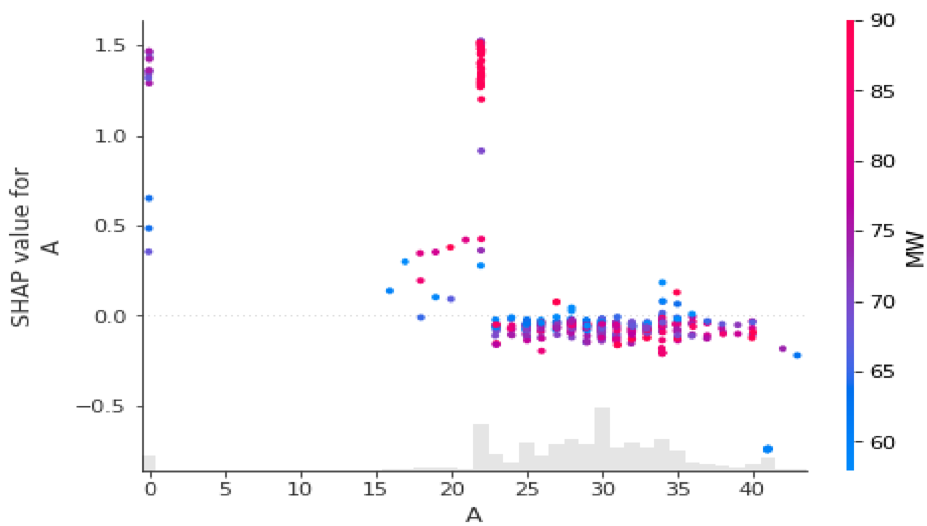

Fig. 10 Heat Map Plot to Predict Maternal Outcome

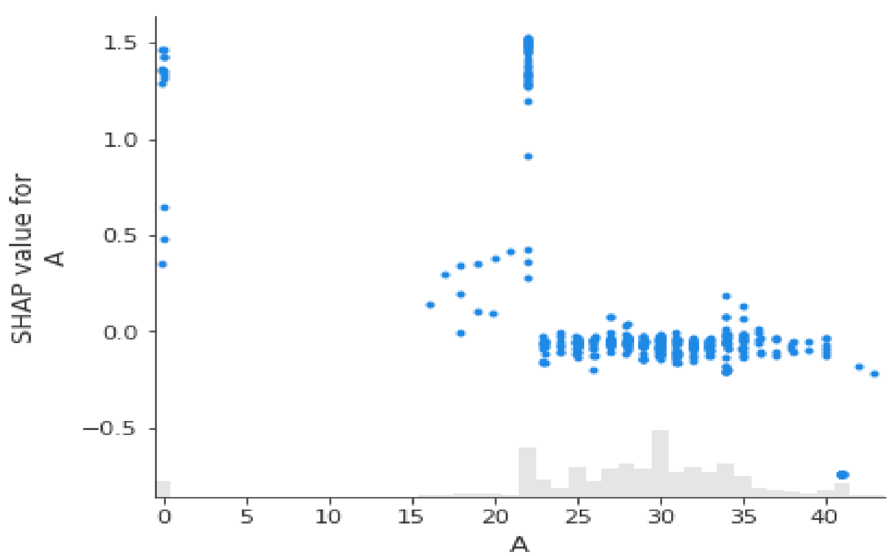

Fig. 11 Heat Map Plot to Predict Maternal Outcome

To show the relationship between the predictors and the outcome

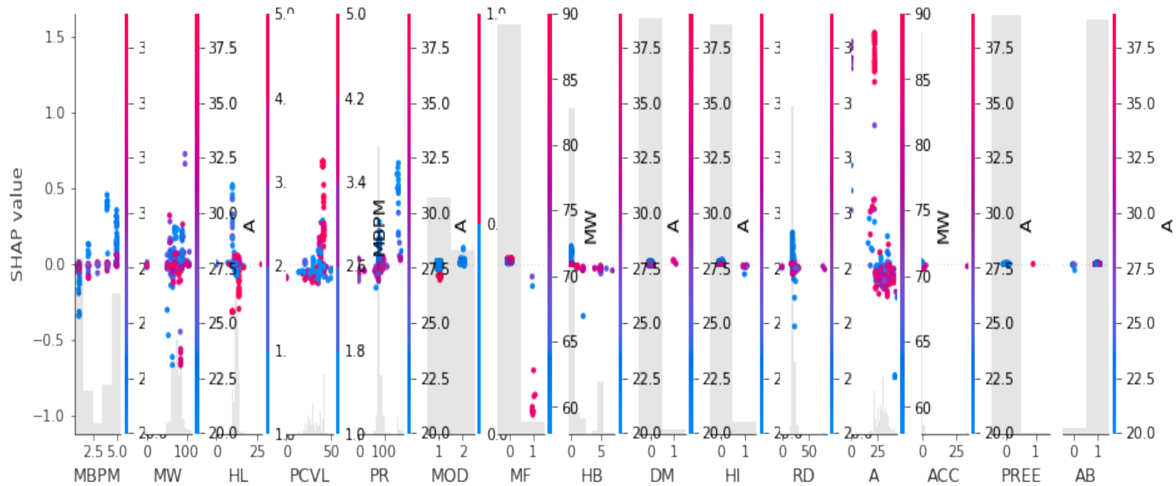

Fig. 12 Scatter Plot to Predict Maternal Outcome

D. The Waterfall Plot

An overview of the dataset on how the feature will be properly manged, using the water fall representation (Figure 13). Stirring the anticipated model output value compared to the prototypical output for maternal outcome across the dataset.

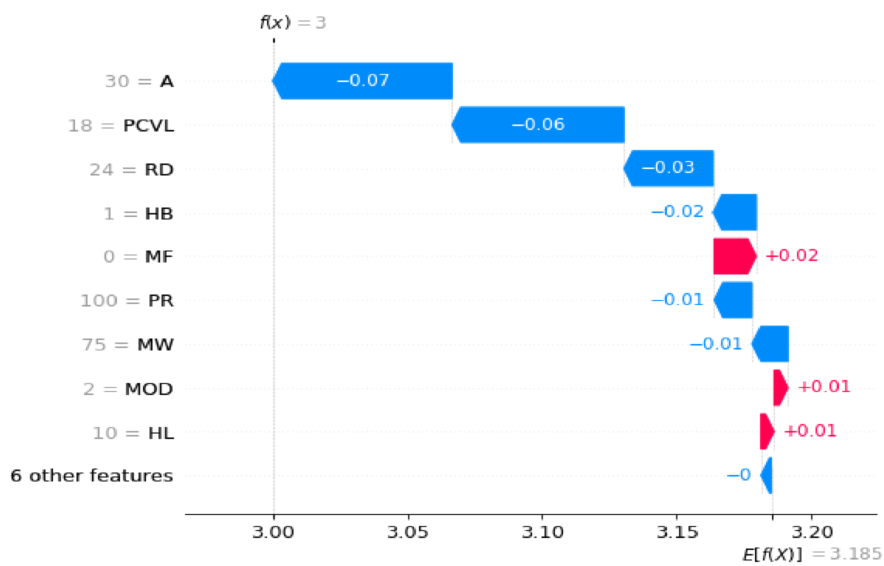

Fig. 13 Waterfall to Predict Maternal Outcome

SHAP values are floating-point integers corresponding to each feature's information in each row. A data point's SHAP value indicates its usefulness in forecasting the results. The data point contributes only slightly to predictions if the SHAP value is significantly closer to zero.

There is no doubt that this work to a large extent have demonstrated the expected features that physicians and non-physicians could be looking out for in a successful maternal outcome. Our work is in line with the works of Guedalia *et al.,* [70], Chill *et al.,* [71]and Hoffman *et al.,* [72] stressed the need to address obstetric complications, their model also reveal that strength of the following features; that a reduced number of prior births, lower frequency of pregnancies, decreased maternal weight, and an advanced gestational week were related with an increased risk of hypertensive disorders during confinement, severe adverse neonatal outcomes and obstetric complications. In summary, the significant features will be summed up in terms of Demography, Laboratory, Physical examination and Mode of delivery.

1. *Demography [73]:* Age and Maternal weight increase can cause infertility and may lead to caesarean section during child birth as well as the occurrence of Down-syndrome (genetic disorder)

2. *Laboratory [74]:* for PCVL and HL, if the result is low or below normal it could lead to anaemia or preterm delivery. However, MF could lead to preterm contraction with resultant preterm delivery.
3. *Physical examination [75]:* MBPM, PR and RD most especially increase in maternal blood pressure preeclampsia and eclampsia that may lead to maternal mortality.
4. *Mode of delivery [76]:* (Vaginal birth, scheduled caesarean, unscheduled caesarean) increased number of caesarean session predisposes one to placenta praevia and increase maternal mortality.

V. CONCLUSION

Machine learning models have remained a useful tool in the last decade due to their computational capabilities. However, many recent works have shifted from predictive models to explainable models. Nevertheless, these advancements have not been fully harnessed from a business and social perspective due to a lack of trust in models, which is centered on their black-box representation. Consequently, in terms of business applications, they could be perceived as less accurate and relatively simple algorithms. Due to these limitations, there is a growing need to adopt explainability and interpretability in machine learning, particularly in Random Forest (RF) models. Our work aims to showcase the strength of the features used in predicting maternal outcomes. Predicting the possibility of maternal outcomes in an interpretable manner would provide doctors with early warnings and help reduce morbidity or mortality rates among women of childbearing age. Thus, this solution may contribute to building a trusted AI model. Despite this significant effort, our work still suffers from some limitations, one of which is the need to explore other methods of explainable AI (XAI). Therefore, it is crucial to compare the SHAP method with other XAI methods such as LIME and CIU in terms of satisfaction, time, and understanding.

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