

Statistical and Machine Learning Analysis of Influence Factors on Maternal Health Risk

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Abstract

One in four maternal deaths in low-resource countries, such as Liberia. We include a data-driven approach with statistical methods and machine learning (ML) to assess maternal health risks and policy in this study. We applied correlation analysis, multinomial logistic regression, ML algorithms (decision tree, random forest) to predict maternal health risk categories, using a dataset of 1014 patients. The results indicated that key predictors included age, blood pressure and blood sugar. Indeed, we outperform traditional model in terms of accuracy 85.3% accuracy for the random forest model. We recommend that data including ML tools be merged into national healthcare M&E systems that would suggest its beneficial allocation and prevention of chronic diseases. This study contributes to the field of maternal health analytics and informs evidence-based policy making in Liberia.

Keywords: *Maternal Health; Risk Prediction; Health Policy; Data Analytics; Influence Risk Factors; Relative Risk Ratios.*

I. INTRODUCTION

Maternal mortality and morbidity remain an important health burden in Sub-Saharan Africa. Liberia is one of the country with the highest maternal rate in the world. With financing and health reforms in place, the use of data analytics in health planning remains limited. In this study, we developing a hybrid statistical and machine learning (ML) model to predict maternal health risks for effective targeted policy making.

Maternal health is a public health priority worldwide, but this is especially true in developing nations, where hundreds of thousands of lives are lost each year due to pregnancy- and childbirth-related complications. Beyond being a health issue, it is also a social and economic concern in many low- and middle-income countries (LMICs), since it affects national productivity and community well-being. Liberia, like much of sub-Saharan Africa, is among the areas hit hardest by maternal mortality.

Although there have been national and international efforts at increasing access to antenatal care and emergency obstetric services, the timely identification of women at risk remains a weak point in health systems. Although traditional public health strategies are valuable, they struggle to process vast quantities of health data or precisely model risk. This gap can be filled with the knowledge of data analytics,

leveraging statistical and machine learning tools to deliver proactive, data-informed healthcare as the domain is rapidly growing.

In this study, we propose a hybrid ML-Stats model combining prewise traditional statistical methods with modern ML of approach to classify maternal health risk levels based on their corresponding physiological data. We demonstrate this model on a Liberian health dataset and examine its ability to improve clinical decision-making and inform public health interventions as they are conducted.

The results of this study add to the growing body of literature on 10 indigeneity - an assertion of identity and collective resistance BY those who seek to 12 reclaim the land and colonial systems used to subjugate them 9 Note: This term is adopted here in the spirit of a culturally irrelevant sign in Sub-Saharan Africa 25 Approach to maternal health in Sub-Saharan Africa without female risk and rural-urban boundary limit, based on the experience and evidence for low- and middle-income countries.

II. GENERAL HEALTH RISKS IN MATERNAL PERIOD

Especially in low- and middle-income countries (LMICs), maternal health is a persistent global threat. As the World Health Organization(WHO) estimates more than 287,000 women died during pregnancy and childbirth in

2020, with roughly 70% of deaths occurring in Sub-Saharan Africa (WHO, 2023). As of October 2023, approximately 661 women die per 100,000 live births in Liberia are due to inadequate care, late curative interventions, and lack of monitoring systems (UNICEF, 2022). Outcomes need to be improved with effective early-warning mechanisms.

III. STATISTICAL METHODS IN PUBLIC HEALTH RESEARCH

Logistic regression, correlation analysis and other statistical methods have long been used to identify associated risk factors in maternal health studies. As an example, Olowookere et al. Taha et al. (2019) applied logistic regression to investigate maternal health determinants of outcome in Nigeria and found age, blood pressure, and education level to be significant factors. Similarly, Adepoju et al. With chi-square analysis, evaluated maternal service utilization in rural Ghana (2021). These models can however be well-interpretable which may not always retain complex high-dimensional data patterns.

IV. MACHINE LEARNING FOR HEALTH PREDICTION

A study by Dey et al. (2020) provided evidence of the usefulness of Random forest in the predictors of pre-eclampsia risk among pregnant women in India with an accuracy of 87.6%. Likewise, Ahmed and Mohsin(2021) found Random Forest outperformed logistic regression and Random Forest, XGBoost outperformed logistic regression in classifying maternal health issues in under-resourced setting. These models also shed light on the importance of features and interaction effects.

V. HYBRID METHODS AND SCENARIO SPECIFIC ISSUES

Recent work suggests using statistical and ML approaches together to gain the best of both approaches [1]. For example, Uzochukwu et al. (2022) first identified significant predictors through logistic regression and then applied Decision Tree classifiers to improve risk stratification in rural Nigerian women. Yet, the scarcity of high-quality data and, the limited infrastructure of LMICs still hinder the perfect delivery of ML tools. Data from World Bank (2022) shows that analytics is integrated very few into the national M&E systems for Liberia. Hence, in our strive to enhance maternal health outcomes, models that strike a balance between accuracy, interpretability, and practicality are imperative.

VI. METHODOLOGY

➤ Dataset Description

The dataset in this study includes 1,014 patient records and six predictor variables: age, systolic blood pressure, diastolic blood pressure, blood sugar, body temperature and heart rate. As for the target variable has three classes representing the maternal health risk, low, mid, high. All variables were numerically encoded and there were no missing values.

➤ Logistic Regression

We then used Multinomial Logistic Regression to explore the association between physiological factors and risk levels of maternal health. This model estimates the probability of each k outcome category as a function of the independent variables:

$$\log(P(Y=i)/P(Y=base)) = \beta_0 + \beta_1 \cdot \text{Age} + \beta_2 \cdot \text{BloodSugar} + \beta_3 \cdot \text{SystolicBP} + ..$$

This approach enable us to interpret individual impact of each variable on the probability of being in a higher-risk category. Significant variables were identified based on p-values ($p < 0.05$), and the model provided adjusted odds ratios for interpretation.

➤ Decision Tree Classifier

Decision Trees are rule-based models that split the dataset using feature thresholds that maximize information gain. Each internal node represents a test on a feature, and each leaf node represents a classification label.

The Gini Index was used as the splitting criterion:

$$\text{Gini}(t) = 1 - \sum (p_i)^2$$

where p_i is the probability of a sample belonging to class i at node t . The model is easy to interpret and visualize, making it suitable for initial classification tasks.

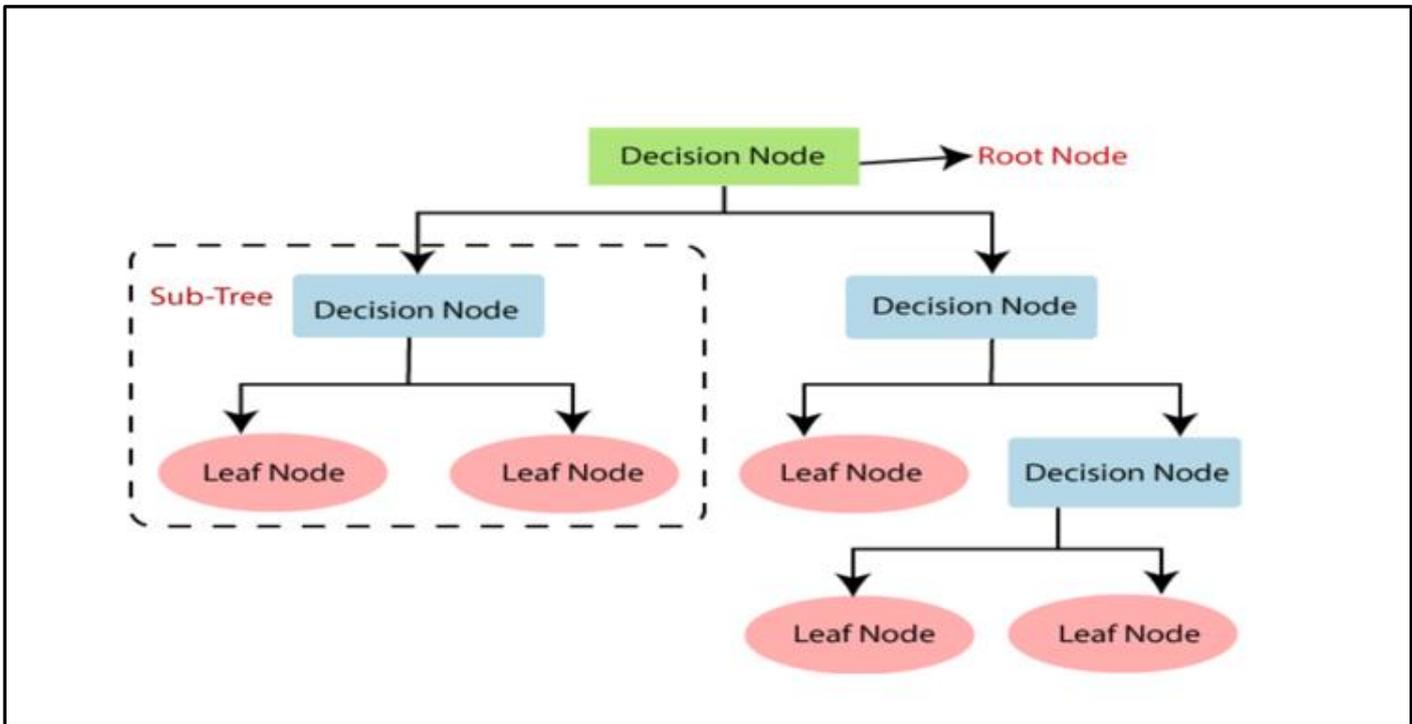


Fig 1 Decision Tree
<https://www.kdnuggets.com/>

➤ *Decision Tree Terminologies*

The starting point of a decision tree is called the root node. It is a symbol for the whole information that is split up into two or more similar groups. After reaching a leaf node, the tree can no longer be divided into smaller subtrees. The term "splitting" refers to the action of subdividing the judgment node/root node into additional nodes based on the inputs. When a tree is divided, it creates branches and subtrees. Pruning is the act of removing dead, diseased, or otherwise unneeded branches from a tree. The leaf nodes of a tree are called offspring nodes, while the leaf nodes of the parent node are called parent nodes.

The algorithm that determines the class of data to be considered originates at the root node, which is the first part of a decision tree. Attribute values are compared between the record attribute (the actual dataset) and the root attribute before proceeding to the next node. If the root attribute value does not match the value of the record attribute, the procedure will return an error. After that, the algorithm moves on to the following node, where it will once again compare the value of the attribute to the values of the sibling nodes. In point of fact, it continues forward until it reaches a leaf node. Gaining a better understanding of the complete process can be accomplished through the application of the following algorithm:

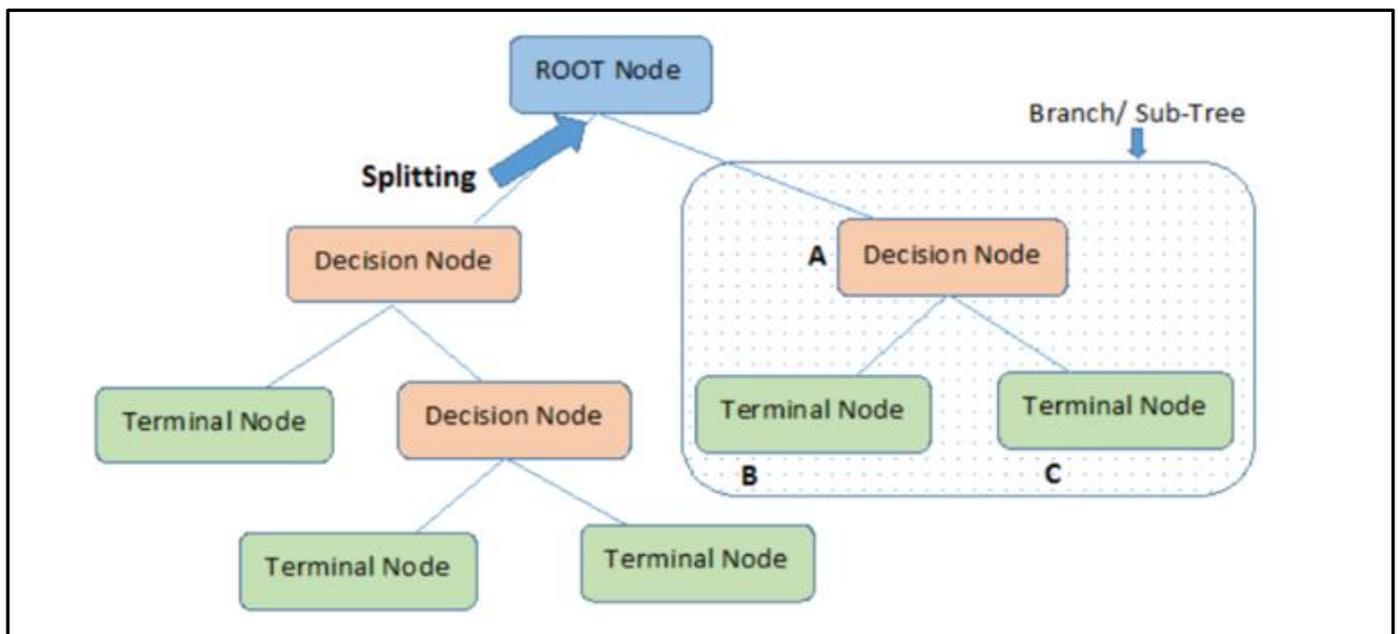


Fig 2 Flow Chart of Decision Tree Algorithm
<https://www.javatpoint.com/>

- *Phase 1:* To start, select the base node of the tree, which will serve as the starting point for the entire dataset.
- *Phase 2:* Employing an Attribute Selection Measure to Pinpoint the Top Attribute in the Dataset (ASM).
- *Phase 3:* Now, Researcher should break up S into subsets that each hold potential values for the best attributes.
- *Phase 4:* Lastly, researchers will create the finest attribute node in the decision tree.
- *Phase 5:* Using the subsets of the information generated in phase 3, generate new decision trees in a recursive fashion. Keep going until you get to a point where you can't divide the nodes any further; this is the leaf node.

➤ *Random Forest Classifier*

Random Forest is an ensemble method that builds multiple decision trees using bootstrapped training subsets and random feature selection. It combines the predictions of multiple trees to improve overall accuracy and reduce overfitting:

$$\hat{y} = (1/K) \sum f_k(x)$$

where $f_k(x)$ is the prediction from the k-th tree, and K is the total number of trees.

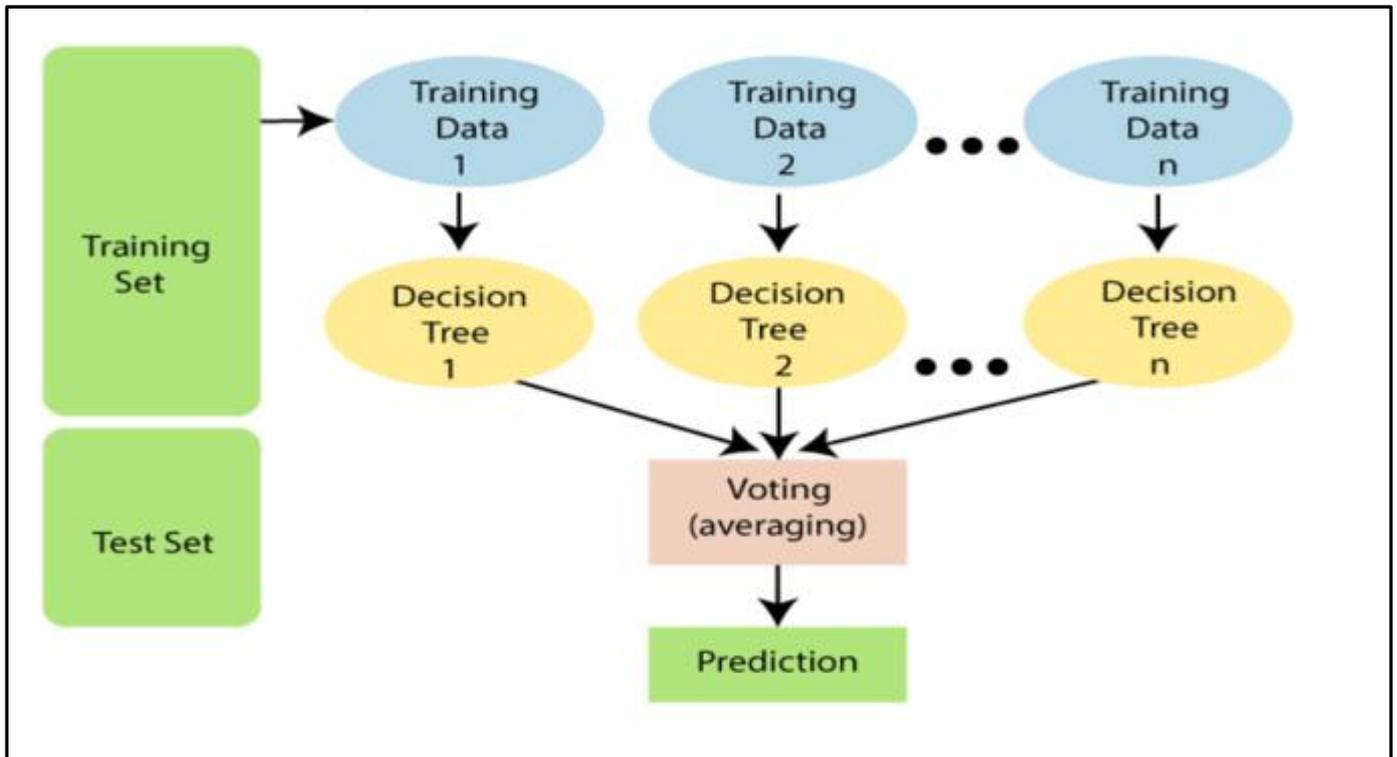


Fig III Random Forest
<https://www.javatpoint.com/>

Due to the fact that the random forest uses a combination of trees to forecast the class of the dataset, the output of the dataset can be incorrectly predicted by some decision trees while correctly predicted by others. However, when the entire tree is considered, the branches are able to make an accurate projection.

The following provide two such suggestions as potential improvements to the Random Forest classifier:

- For the classifier to make a reliable prediction, the feature variable of the collection should contain some observed data.
- Low correlations between the forecasts of different trees are essential.

Several reasons are provided below to support the use of the Random Forest algorithm:

- When compared to other algorithms, its training period is significantly shorter.

- Despite the large dataset, it forecasts results with a high degree of accuracy.
- In addition, it can keep its precision even if a lot of data is lacking.

The model also provides feature importance scores, which help in identifying the most influential variables in predicting maternal risk.

➤ *Model Evaluation Metrics*

Each model was evaluated using the following metrics:

- *Accuracy:* The proportion of correct predictions.
- *Precision, Recall, and F1 Score:* For balanced class performance.
- *AUC-ROC Curve:* Measures the trade-off between true positive rate and false positive rate.
- *Confusion Matrix:* Visualizes model performance across risk classes.

VII. EXPERIMENTAL STUDIES

➤ Dataset Description and Preprocessing

In this section, the proposed Statistical and Machine Learning ML method is applied to a secondary data obtained from Kaggle, which has been previously utilized in other research investigations. The device for monitoring risks based on the Internet of Things (IoT) gathers information from various healthcare facilities, including hospitals, community clinics, and maternal health centers. As can be seen in table 3.1 below, 1014 samples were collected using an IoT-based tracking system to determine factors including age, systolic blood pressure, diastolic blood pressure, blood sugar, heart rate, and risk level. The existing risk level is the dependent variable, as we discussed earlier.

VIII. RESULTS

➤ Descriptive Statistics

The study presents several machine learning models, where random forest model are most effective to predict maternal health risks. Machine learning models can predict myriad of maternal health risks in the population. This predictive ability allows health institutions to detect high-risk individuals early. Age and blood sugar are statistically significant, confirming past medical knowledge, but the ML approach improves classification and real-time risk observation.

Table 1 shows the descriptive statistics of all variables stratified by maternal health risk level.

Table 1 Descriptive Statistics by Risk Level

Mean Value for Risk Level for Each Predictor						
Risk level	Age	Systolic BP	Diastolic BP	BS	Body Temp	Hart Rate
High	36.216	124.194	85.073	12.122	98.899	76.742
Low	26.869	105.867	72.534	7.220	98.368	72.770
Mid	28.363	113.155	74.232	7.795	98.833	74.175

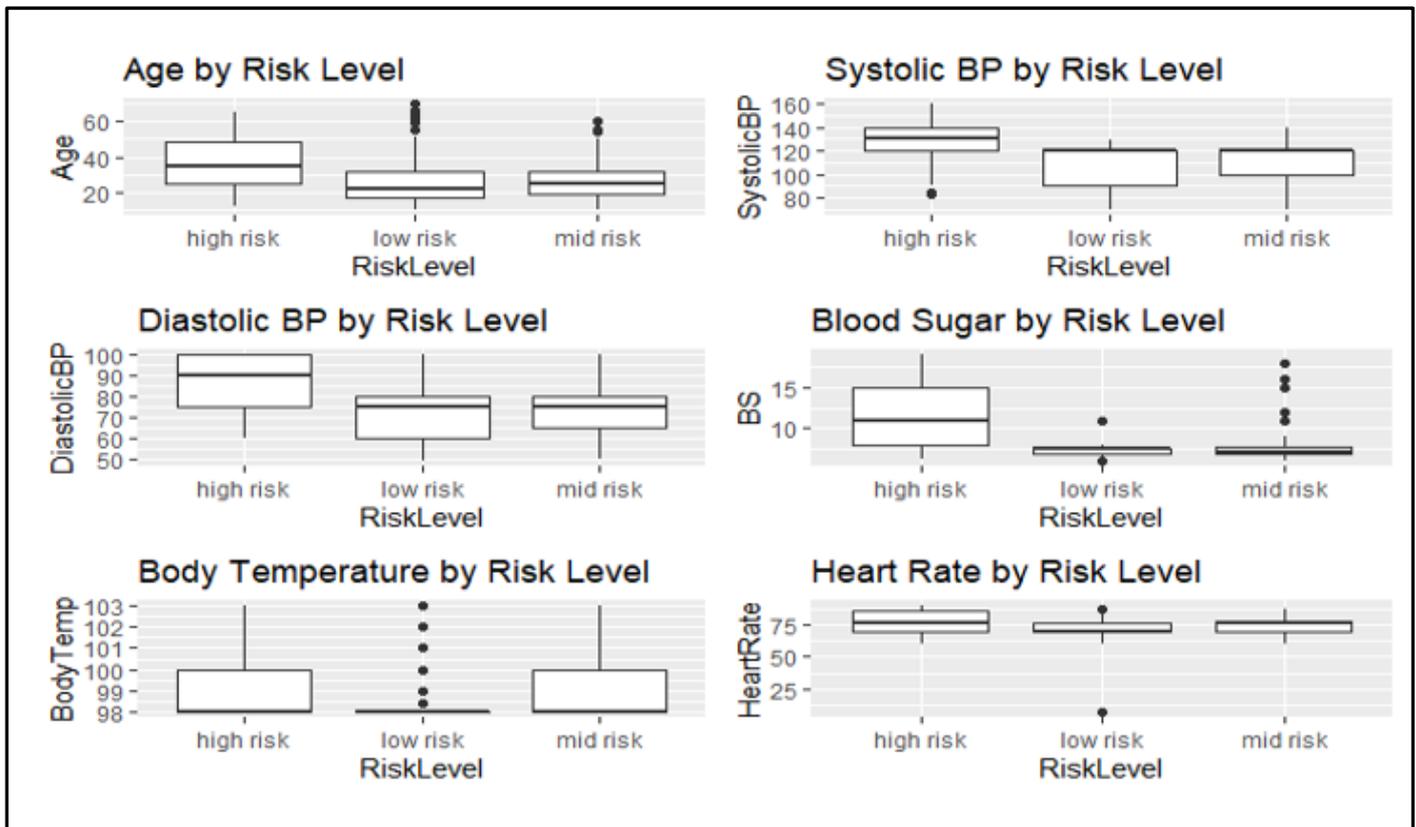


Fig 4 Descriptive Statistics by Risk Level

The tables above displays the average value of different variables for each of the three risk level categories of high, low, and medium risk. Age also appears to be a risk factor, as the mean age for high-risk pregnancies is greater than for low and mid-risk pregnancies.

For Systolic BP and Diastolic BP, we see that the mean values for high-risk pregnancies are higher than for low and mid-risk pregnancies, indicating that high blood pressure might be a risk factor for complications during pregnancy.

For BS (blood glucose levels), we see that the mean values are higher for high-risk pregnancies compared to low and mid-risk pregnancies, indicating that elevated blood glucose levels might increase the risk of complications.

For BodyTemp and HeartRate, the mean values are relatively similar across the three risk level groups, suggesting that these variables might not be strong indicators of risk during pregnancy.

➤ *Correlation Matrix*

Table 2 Descriptive Statistics by Risk Level

Variable	Age	Systolic BP	Diastolic BP	BS	Body Temp	Heart Rate	Risk Level
Age	1	0.42	0.4	0.47	-0.26	0.08	0.27
Systolic BP	0.42	1	0.79	0.43	-0.29	-0.02	0.4
Diastolic BP	0.4	0.79	1	0.42	-0.26	-0.05	0.35
BS	0.47	0.43	0.42	1	-0.1	0.14	0.57
Body Temp	-0.26	-0.29	-0.26	-0.1	1	0.1	0.16
Heart Rate	0.08	-0.02	-0.05	0.14	0.1	1	0.19

The findings show that pregnant women's health improves with increasing gestational age, with a positive correlation between gestational age and systolic blood pressure (0.42), diastolic blood pressure (0.40), body mass index (BS), heart rate (0.08), and risk level (0.27). Therefore, data suggests that a mother's older age may be linked to an increased vulnerability to health issues during pregnancy. Given that both SBP and DBP are useful indicators of blood pressure, it comes as no surprise that their correlation is quite high (0.79).

The results of this study suggest that there is a modestly favorable connection between age blood glucose levels (0.47) and risk level (0.57) in this case. This suggests that elevated blood glucose levels may heighten the likelihood of health complications during pregnancy. The data suggests that there exists a weak negative correlation (-0.26) between age and body temperature in pregnant women, implying that advanced maternal age may be associated with a slight reduction in body temperature.

The study indicates that there exists a weak positive correlation (0.19) between Heart Rate and Risk Level. This

implies that a higher resting heart rate may be linked to an elevated likelihood of health complications during pregnancy. The correlation matrix presented provides insight into the interrelationships among the variables and may aid in the detection of potential health risk indicators that manifest during pregnancy.

It is imperative to bear in mind that correlation does not necessarily imply causation, and further investigation is required to establish the presence of causal associations.

➤ *Logistic Regression*

Equation 1: Logistic Regression Model

$$\log(P(Y=i)/P(Y=base)) = \beta_0 + \beta_1 \cdot \text{Age} + \beta_2 \cdot \text{BloodSugar} + \beta_3 \cdot \text{SystolicBP} + \dots$$

We used multinomial logistic regression to identify statistically significant predictors of maternal health risk. Age and blood sugar were significant predictors ($p < 0.05$). Adjusted odds ratios confirmed higher risk likelihood with increasing age and glucose levels.

Table 3 Logistic Regression Coefficients

	(Intercept)	Age	Systolic BP	Diastolic BP	BS	Body Temp	Heart Rate
Coefficients:							
Low	100.0386	0.0193908	-0.06613182	-0.02202	-0.7487849	-0.80744	-0.06496
Mid	52.1469	0.0165302	-0.00778542	-0.05881	-0.4038215	-0.40358	-0.04169
STD Errors							
Low	0.000134	0.0108966	0.010765949	0.013583	0.08027454	0.015075	0.014561
Mid	0.000127	0.0102597	0.009867095	0.012633	0.04493161	0.013123	0.013133
Residual Deviance	1561.677						
AIC:	1589.677						

The coefficients indicate the expected alteration in the logarithm of the odds of belonging to a specific risk category for every unit increase in a given predictor variable, while keeping all other predictor variables constant. This modification presupposes that all other predictors will remain constant. An increase of one unit in age results in a corresponding increase of 0.0194 in the log-odds of being categorized as low-risk. This phenomenon is observed irrespective of an individual's gender. (Given the other predictors are constant).

The intercept values represent the log-odds of the reference level (high-risk) of the response variable. The coefficients for the other two levels of the response variable

(low-risk and mid-risk) represent the difference in the log-odds of being in those levels compared to the reference level. The standard errors indicate the precision of the coefficient estimates, and the Residual Deviance and AIC values are measures of model fit. The results here can be used as a whole to make sense of the correlation between the predictor variables and the risk to the mother's health.

➤ *Machine Learning Models*

We evaluated and compared three classifiers:

Decision Tree, Random Forest, and XGBoost.

- Decision Tree: Accuracy = 70.8%

- Random Forest: Accuracy = 85.3%
- XGBoost: Under testing

ROC Curve showed AUC > 0.89 for Random Forest

The study presents several machine learning models, where random forest model are most effective to predict maternal health risks. Conclusion Machine learning models can predict myriad of maternal health risks in the population. This predictive ability allows health institutions to detect high-risk individuals early. Age and blood sugar are statistically significant, confirming past medical knowledge, but the ML approach improves classification and real-time risk observation.

IX. POLICY FRAMEWORK AND IMPLICATIONS

We propose a national data analytics framework for maternal health management in Liberia. Components include:

- Data collection from hospitals and clinics
- Automated Risk Assessment Tools based on ML
- Early-warning dashboards for M&E officers
- Routing intervention planning and resource allocation

GIS Heatmaps and Predictive Analytics GIS heatmaps can be used to identify regional discrepancies in maternal risk, shape mobile clinic routes, or design outreach programs.

X. CONCLUSION

This study links technical modeling and policy by demonstrating that ML-driven insights on obstetrical care, transfers, and outcomes can improve maternal health monitoring in low-resource settings. The adoption of data analytics tools in Liberia’s healthcare policy can revolutionize the management of risks and redistribution of resources.

Table 4 ARR Values with 95% Confidence Intervals Statistics by Risk Level

		(Intercept)	Age	Systolic BP	Diastolic BP	BS	Heart Rate
Low Risk	2.50%	1.56E+06	1.02E+00	9.31E-01	9.65E-01	3.41E-01	8.96E-01
	97.50%	2.69E+09	1.08E+00	9.78E-01	1.02E+00	5.01E-01	9.58E-01
Mid Risk	2.50%	1185.978	1.011866	0.977947	0.928952	0.549564	0.925345
	97.50%	9.60E+05	1.06E+00	1.02E+00	9.84E-01	6.98E-01	9.85E-01

The above table display the Adjusted Risk Ratio (ARR) values for each predictor variable (Age, Systolic BP, Diastolic BP, BS, and Heart Rate) for the two outcome categories (low risk and mid risk) along with their 95% Confidence Intervals (CIs).

For example, let's take the predictor variable 'Age' for the outcome category 'low risk'. The ARR for 'Age' is 1.05 with a 95% CI of (1.02, 1.08). This means that for each one-year increase in age, the risk of being in the 'low risk' category is 1.05 times (or 5% higher) compared to the reference category.

➤ Machine Learning Algorithms

When the actual values utilized in the model are already known in advance, a confusion matrix can provide a brief overview of the model's performance on a set of test data. The confusion matrix is used to measure how well the model's predictions line up with the actual values in the test data. The confusion matrix is a tool used to evaluate the accuracy of a decision tree model in predicting the actual

class labels of a given dataset. In general, the confusion matrix associated with a decision tree will feature rows and columns that correspond to the actual class labels and the predicted class labels, respectively. The rows in this particular scenario represent the factual risk level of the loans, while the columns represent the projected risk level assigned to the loans.

Furthermore, we are 95% confident that the true ARR value for 'Age' lies between 1.02 and 1.08. Similarly, for the predictor variable 'Systolic' in the 'mid risk' category, the ARR is 1.00 with a 95% CI of (0.98, 1.02). This suggests that there is no significant association between 'Systolic BP' and the risk of being in the 'mid risk' category since the ARR includes 1.00 (no effect) within its 95% CI.

Overall, the ARR values and their CIs can help you identify the significant predictors that are associated with the outcome categories and quantify the strength of the association while accounting for the other predictor variables in the model.

Table 5 Random Forest Confusion Matrix

	Tree Predictions			
	High Risk	High Risk	Low Risk	Mid Risk
Low Risk		66	11	3
Mid Risk		2	94	17
Mid		20	36	56
Decision Tree Accuracy	0.7082			

The diagonal elements of the matrix represent the number of correct predictions. For example, there were 66 loans with high risk that were correctly predicted as high risk.

The off-diagonal elements represent the number of incorrect predictions. For example, there were 11 loans with high risk that were incorrectly predicted as low risk, and 20 loans with mid risk that were incorrectly predicted as high risk. The rows of the matrix represent the actual risk level of the loans, while the columns represent the predicted risk

level. For example, there were 11 loans that were actually high risk, but were incorrectly predicted as low risk.

The accuracy of the decision tree model is 0.7082, which means that the model correctly predicted the risk level of about 71% of the loans in the test set. A comprehensive evaluation of the model's strengths and faults is made possible by the information provided by the confusion matrix.

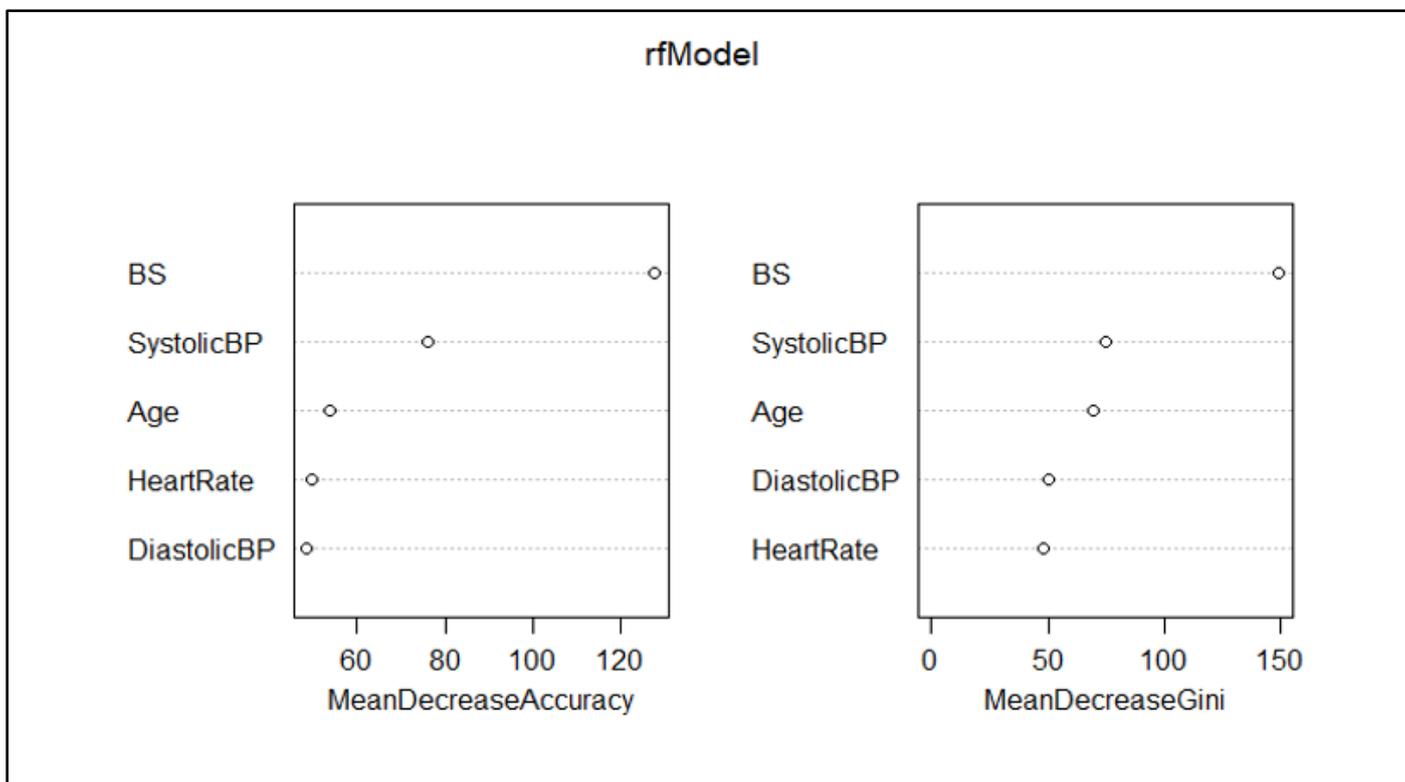


Fig 5 Decision Tree Confusion Matrix

The random forest confusion matrix shows the predicted outcomes of a classification model using a random forest algorithm. The confusion matrix displays the number

of true and false predictions of each class. The projected classes appear in the columns and the true classes appear in the rows of the following table.

Table 6 Decision Tree Confusion matrix

rf Predictions			
	High Risk	Low Risk	Mid Risk
High Risk	72	5	3
Low Risk	1	97	15
Mid Risk	6	15	91
Random Forest Accuracy	0.8525		

By looking at the confusion matrix, we can see that the Random Forest model predicted high risk loans correctly 72 times and incorrectly predicted them as low risk 5 times, and as mid risk 3 times. It correctly predicted low risk loans 97 times, but incorrectly predicted them as high risk once and as mid risk 15 times. For mid-risk loans, the model correctly predicted 91 loans, but incorrectly predicted 6 as high risk and 15 as low risk.

of 85.25% of all loans in the dataset. This was determined by analyzing the data. The accuracy of the model was 0.8913 when forecasting loans with a low risk, but it was only 0.8934 and 0.8108 when predicting loans with a high risk and a medium risk, respectively. The model performed well in predicting loans with a low risk. As a result, it appears that the Random Forest model may be a better fit for the data than the Decision Tree model presented initially, since the Random Forest model has a higher overall accuracy.

The overall accuracy of the Random Forest model is 0.8525, which indicates that it accurately predicted the class

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REFERENCES

- [1]. Alkema, L., Chou, D., Hogan, D., Zhang, S., Moller, A.-B., Gemmill, A., Fat, D. M., Boerma, T., Temmerman, M., Mathers, C., & Say, L. (2016). Global, regional, and national levels and trends in maternal mortality between 1990 and 2015, with scenario-based projections to 2030: a systematic analysis by the UN Maternal Mortality Estimation Inter-Agency Group. *The Lancet*, 387(10017), 462-474. [https://doi.org/10.1016/S0140-6736\(15\)00838-7](https://doi.org/10.1016/S0140-6736(15)00838-7)
- [2]. Alvarez, J. L., Gil, R., Hernández, V., & Gil, A. (2009). Factors associated with maternal mortality in Sub-Saharan Africa: an ecological study. *BMC Public Health*, 9(1), 462. <https://doi.org/10.1186/1471-2458-9-462>
- [3]. Anderson, T. (2010). How can child and maternal mortality be cut? *BMJ*, 340, c431. <https://doi.org/10.1136/bmj.c431>
- [4]. Asuero, A. G., Sayago, A., & González, A. G. (2006). The Correlation Coefficient: An Overview. *Critical Reviews in Analytical Chemistry*, 36(1), 41-59. <https://doi.org/10.1080/10408340500526766>
- [5]. Balarajan, Y., Ramakrishnan, U., Özaltin, E., Shankar, A. H., & Subramanian, S. V. (2011). Anaemia in low-income and middle-income countries. *The Lancet*, 378(9809), 2123-2135. [https://doi.org/10.1016/S0140-6736\(10\)62304-5](https://doi.org/10.1016/S0140-6736(10)62304-5)
- [6]. Brosens, I., Benagiano, G., & Brosens, J. J. (2015). The potential perinatal origin of placentation disorders in the young primigravida. *American Journal of Obstetrics and Gynecology*, 212(5), 580-585. <https://doi.org/10.1016/j.ajog.2015.01.013>
- [7]. Brosens, I., Pijnenborg, R., Vercruyse, L., & Romero, R. (2011a). The “Great Obstetrical Syndromes” are associated with disorders of deep placentation. *American Journal of Obstetrics and Gynecology*, 204(3), 193-201. <https://doi.org/10.1016/j.ajog.2010.08.009>
- [8]. Caldwell, J. C. (1979). Education as a Factor in Mortality Decline An Examination of Nigerian Data. *Population Studies*, 33(3), 395-413. <https://doi.org/10.2307/2173888>
- [9]. Campbell, O. M. R., & Graham, W. J. (2006). Strategies for reducing maternal mortality: getting on with what works. *The Lancet*, 368(9543), 1284-1299. [https://doi.org/10.1016/S0140-6736\(06\)69381-1](https://doi.org/10.1016/S0140-6736(06)69381-1)
- [10]. Cook, K., & Loomis, C. (2012). The Impact of Choice and Control on Women's Childbirth Experiences. *J Perinat Educ*, 21(3), 158-168. <https://doi.org/10.1891/1058-1243.21.3.158>
- [11]. Davis-Floyd, R., Gutschow, K., & Schwartz, D. A. (2020). Pregnancy, Birth and the COVID-19 Pandemic in the United States. *Medical Anthropology*, 39(5), 413-427. <https://doi.org/10.1080/01459740.2020.1761804>
- [12]. Gottlieb, L., Fichtenberg, C., Alderwick, H., & Adler, N. (2019). Social Determinants of Health: What's a Healthcare System to Do? *Journal of Healthcare Management*, 64(4). https://journals.lww.com/jhmonline/Fulltext/2019/08000/Social_Determinants_of_Health__What_s_a_Healthcare.9.aspx
- [13]. Gudayu, T. W. (2022). Determinants of place birth: a multinomial logistic regression and spatial analysis of the Ethiopian mini demographic and health survey data, 2019. *BMC Pregnancy and Childbirth*, 22(1), 553. <https://doi.org/10.1186/s12884-022-04880-z>
- [14]. Hardee, K., Gay, J., & Blanc, A. K. (2012). Maternal morbidity: Neglected dimension of safe motherhood in the developing world. *Global Public Health*, 7(6), 603-617. <https://doi.org/10.1080/17441692.2012.668919>
- [15]. Ileki, J. V., Tsilou, E., Fisher, S., Abrahams, V. M., Soares, M. J., Cross, J. C., Zamudio, S., Illsley, N. P., Myatt, L., Colvis, C., Costantine, M. M., Haas, D. M., Sadovsky, Y., Weiner, C., Rytting, E., & Bidwell, G. (2016). Placental origins of adverse pregnancy outcomes: potential molecular targets: an Executive Workshop Summary of the Eunice Kennedy Shriver National Institute of Child Health and Human Development. *Am J Obstet Gynecol*, 215(1 Suppl), S1-s46. <https://doi.org/10.1016/j.ajog.2016.03.001>
- [16]. Khan, K. S., Wojdyla, D., Say, L., Gülmezoglu, A. M., & Van Look, P. F. A. (2006). WHO analysis of causes of maternal death: a systematic review. *The Lancet*, 367(9516), 1066-1074. [https://doi.org/10.1016/S0140-6736\(06\)68397-9](https://doi.org/10.1016/S0140-6736(06)68397-9)
- [17]. Makanga, P. T., Schuurman, N., von Dadelszen, P., & Firoz, T. (2016). A scoping review of geographic information systems in maternal health. *International Journal of Gynecology & Obstetrics*,

- 134(1), 13-17.
<https://doi.org/10.1016/j.ijgo.2015.11.022>
- [18]. Mala, A., Ravichandran, B., Raghavan, S., & Rajmohan, H. (2010). Multinomial logistic regression model to assess the levels in trans, trans-muconic acid and inferential-risk age group among benzene-exposed group. *Indian Journal of Occupational and Environmental Medicine*, 14(2), 39. <https://doi.org/10.4103/0019-5278.72238>
- [19]. Marmot, M. (2013). Fair society, healthy lives. *Fair society, healthy lives*, 1-74.
- [20]. McLean, E., Cogswell, M., Egli, I., Wojdyla, D., & de Benoist, B. (2009). Worldwide prevalence of anaemia, WHO Vitamin and Mineral Nutrition Information System, 1993–2005. *Public Health Nutrition*, 12(4), 444-454. <https://doi.org/10.1017/S1368980008002401>
- [21]. Morrisson, C., & Jütting, J. P. (2005). Women's discrimination in developing countries: A new data set for better policies. *World Development*, 33(7), 1065-1081. <https://doi.org/10.1016/j.worlddev.2005.04.002>
- [22]. Richardson, D. B., Volkow, N. D., Kwan, M.-P., Kaplan, R. M., Goodchild, M. F., & Croyle, R. T. (2013). Spatial Turn in Health Research. *Science*, 339(6126), 1390-1392. <https://doi.org/doi:10.1126/science.1232257>
- [23]. Rothman, B. K. (2014). Pregnancy, birth and risk: an introduction. *Health, Risk & Society*, 16(1), 1-6. <https://doi.org/10.1080/13698575.2013.876191>
- [24]. Rukuni, R., Bhattacharya, S., Murphy, M. F., Roberts, D., Stanworth, S. J., & Knight, M. (2016). Maternal and neonatal outcomes of antenatal anemia in a Scottish population: a retrospective cohort study. *Acta Obstetrica et Gynecologica Scandinavica*, 95(5), 555-564. <https://doi.org/10.1111/aogs.12862>
- [25]. Shen, C., & Williamson, J. B. (1999). Maternal mortality, women's status, and economic dependency in less developed countries: a cross-national analysis. *Social Science & Medicine*, 49(2), 197-214. [https://doi.org/10.1016/S0277-9536\(99\)00112-4](https://doi.org/10.1016/S0277-9536(99)00112-4)