

MACHINE LEARNING PREDICTIVE MODEL FOR MATERNAL MORTALITY IN KENYA

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Abstract

The rate of maternal mortality in Kenya is alarming and brings a primary public health concern, as it stands at 342 deaths per 100,000 live births, which exceeds the global mortality rate of 211. Approximately 5000 women lose their lives annually to pregnancy complications, and about 40 percent of these women have associated risk factors that include maternal age, parity, pre-existing conditions, home residence, and socio-economic factors. The remaining 60 percent is due to avoidable causes, which can be addressed through early interventions. This study sought to fix this prevailing problem by developing a predictive model of maternal mortality based on electronic medical records (EMRs) using a machine learning technique. A sample of 500,000 representative birth records from the Kenya Health Information System (KHIS) that was enclosed in more than 1.2 million births that were reported in the year 2022 was cleaned and analyzed using Python libraries, namely Pandas, NumPy, Seaborn, and Scikit-learn, to perform data processing, computation, visualization, and model training, respectively. Based on the principles of Eric Topol of predictive care in machine learning, which implies the improvement of the quality of diagnostics, the possibility to intervene before the beginning of disease progression, and the ability to make clinical decisions based on data, four models were implemented and tested, namely Logistic Regression (LR), Random Forest (RF), Support Vector Machine (SVM), and Extreme Gradient Boosting (XGBoost). The accuracy, precision, recall, F1-score, and ROC-AUC were applied to measure the performance of models. XGBoost performed better than all other models, with the result of 0.89 accuracy, 0.87 precision score, 0.92 recall, 0.89 F1-score, and 0.90 ROC-AUC value, thus indicating the efficacy of an ensemble learning categorization in learning complex non-linearities on maternal health data. In the study, the authors describe the promise of predictive modeling to make early-stage risk detection, facilitate timely interventions, improve allocations of resources, and support evidence-based policymaking. The results back the idea of implementing machine learning in Kenya's hospital-based decision support systems (DSS) to improve maternal health.

Keywords: Maternal Mortality Rate, Predictive Modeling, Receiver Operating Characteristic-Area Under Curve (ROC-AUC), F1-Score, Ensemble Model.

Introduction

Maternal mortality is a serious health issue of concern in the world, with developing nations being the worst affected. The World Health Organization (WHO) highlights that the region of Sub-Saharan Africa has two-thirds of the 295,000

maternal deaths that have been recorded in 2017. The situation in Kenya is not much better, where the maternal mortality ratio (MMR) is 342 deaths per 100,000 live births, which would translate to roughly 5,000 deaths a year even when interventions in the country are taken into account,

including the provision of free maternity services or the training of skilled birth attendants (Wu et al., 2020; UNFPA, 2023). At the same time, there is a growing number of electronic medical records (EMRs) being adopted, as the number of facilities with some EMR reached 67% in public facilities and 89% in the private sector (Insight, 2022); predictive analytics and machine learning (ML) are not fully deployed yet. Most responses to treatment for healthcare issues are results where the therapy occurs once a complication has been established. However, valuable information can be found in EMRs, and maternal care can be diverted to a proactive, data-driven concept (Oduma, 2020).

The study addressed a vital gap because it used the Kenyan EMR data and designed a localized ML model to predict maternal deaths. Despite the success of using predictive models (e.g., logistic regression, random forest, support vector machines (SVM), and XGBoost) to predict conditions such as preeclampsia and postpartum hemorrhage (Al-Rubaie et al., 2020; Li et al., 2021a), the majority of them are implemented in high-resource facilities. Such models are not very applicable in low- and middle-income countries (LMICs), such as Kenya, where the socioeconomic differences, infrastructural gaps, and disease burden determine maternal productivity.

The issues of maternal mortality in Kenya reflect the larger gaps in the world. Ideally, even though the MMR fell globally by 34 percent, or 342 to 221 deaths per 100,000 live births in the same periods of 2000 and 2020, in Sub-Saharan Africa it is reported that 544 die per 100,000 live births, compared to only 19 in Europe and Central Asia (WHO, 2023; UNICEF, 2023). In Kenya, hemorrhage (34%), sepsis (16%), hypertensive disorders (9%), obstructed labor (12%), and unsafe abortion (8%) are still dominant factors, as their impact is worsened by poverty, low level of education, and remote access to emergency obstetric care (UNICEF, 2023; UNFPA, 2023).

Research within the last decade worldwide has revealed the potential of ML in the field of maternal health. For example, Li et al. (2021b) demonstrated

that XGBoost came out with an AUROC of 95.5% to predict preeclampsia. Likewise, CatBoost was utilized to predict postpartum type 2 diabetes with great precision by Kumar et al. (2021). Among LMICs, models that predict preterm labor and low birth weight with good performance were developed using local data by other researchers, such as Raja et al. (2021) in India or Bekele (2022) in Ethiopia.

Kenya, however, falls behind in embracing such tools. Remarkably, current local research, as in the case of Sharon (2022), has been aimed at predicting other child-related outcomes, like low birth weights, instead of childbirth mortality. Additionally, most models have not been adjusted to Kenya's socio-economic and healthcare context (Mwaura et al., 2024). This study supports the evidence of predictive modeling as a paradigm shift in line with Sustainable Development Goal 3.1, which aims to decrease the amount of global MMR to less than 70 deaths per 100,000 population by 2030. It will allow early risk identification, intervention at the appropriate time, resources, and evidence-based decision-making to enhance maternal health outcomes in Kenya. The findings from this study justify the need to integrate machine learning into hospital-based decision support systems (DSS) to improve the health outcomes of mothers in Kenya.

Research Methodology

The study used a mixed-methods design that entailed exploratory data analysis (EDA) and observational-analytical modeling with a quantitative paradigm. The exploratory process strictly explored maternal health trends and mother-child profile observations using a second-level, large-scale data set from the Kenya Health Information System (KHIS) database. The exploratory analysis identified notable descriptive tendencies, associations, and inter-variable relations, which were presented using heatmaps and correlation matrices. These observations were used to inform the selection of variables and form the foundation for constructing the predictive modeling. The observational aspect, which was

retrospective in scope, involved training and validating four supervised machine learning algorithms to forecast maternal mortality based on identified risk factors. The pertinent predictive variables were obtained, processed, and used to train the supervised algorithms, with the model's performance assessed using standard criteria for classification.

The study used Electronic Medical Records (EMR) of pregnant women, extracted from the Kenya Health Information System (KHIS). The study was explicitly aimed at women between the ages of 18 and 45 years, a category in line with the significant years of bearing children, while incorporating heightened pregnancy risks beyond this age (Zhai et al., 2021). Specifically noted was only inclusion in cases where gestational age was above 24 weeks, acknowledging this to be the time of viability of the fetus beyond the womb. This criterion for selection was to guarantee valid prediction results for the mother mortality as 24 weeks gestational age means the child is viable to survive outside the womb.

The study used a population of all women who delivered in Kenya's healthcare system in the year 2022, representing a total of about 1.2 million births. Out of these, 1,208,846 births were in hospitals and were thus readily available in KHIS. The data met the definition of characteristics of big data, the three Vs: volume, velocity, and variety, making them applicable in machine learning paradigms, as highlighted by Paullada et al. (2021). For computational purposes, a subset of 500,000 records was selected for analysis to meet inclusion criteria and preserve data integrity. A census strategy was employed in this study so that the entire available and eligible set of 500,000 records was used. This strategy ensured full utilization of available data, reduced sampling bias to a minimum, and could pick up even those rare but crucial mother-infant health indicators. Referring to Althubaiti (2023), a census strategy is most suitable when dealing with a manageable population and when accurate data-driven decisions, such as predictive health modeling, are necessary.

The primary data was derived from the Kenya Health Information System (KHIS). After derivation, the data was examined to obtain significant insights into several feature categories: demographic information, which were age, educational attainment, revenue, and geographical location; health information, which were birth weight, immunization status, pregnancy-related health history, and behavioral information such as drug and alcohol abuse. The variables represented the core characteristics employed in all data analysis periods and the study's predictive modeling.

The data was standardized in post-collection after data extraction to reconcile differences across sources. For example, differing thresholds for gestational diabetes diagnosis were standardized using Python's StandardScaler in the sklearn preprocessing module, rescaling to a mean of 0 and a standard deviation of 1. Subsequently, intensive data validation was conducted to detect and fix discrepancies, outliers, and gaps. Automated validation rules detected outliers like impossible birth weights. Additionally, cross-verification was conducted, that is, by cross-checking birth weights and gestational age to known medical ranges. Missing data were filled by imputation techniques: mean imputation was applied to continuous measures like birth weight, and mode imputation was applied to categorical variables. Finally, potential sources of bias were detected and corrected, particularly because different hospitals provided care to other demographic groups. For example, if a hospital with a majority concentration of low-income patients was compared to a wealthier community hospital, stratification based on socioeconomic group balanced the dataset to facilitate broader generalizability to Kenya's population.

The data obtained from KHIS was exported in a CSV format and analyzed by descriptive statistics. Results were presented in summary bar graphs for the maternal trends and data visualizations depicting the interaction between various maternal indicators with the Matplotlib library. Descriptive analysis helped in gaining a groundwork-based

insight about maternal-child health trends and helped in identifying important risk-prediction factors to model. For observational studies in the data design phase, supervised machine learning algorithms were trained to forecast maternal and child mortality outcome variables: Logistic Regression (LR), Random Forest (RF), Support Vector Machine (SVM), and Extreme Gradient Boosting (XGBoost). The dataset of 500,000 records (data points) was split into training and test sets by applying machine learning's 80/20 technique. Additionally, model performance was tested with measures such as accuracy, precision, recall, ROC-AUC, and F1 score since these are the best-fit performance measures when there is a binary classification. Hyperparameter tuning and model optimization were used to fine-tune model outputs and cross-validation was used to ensure model stability and reliability.

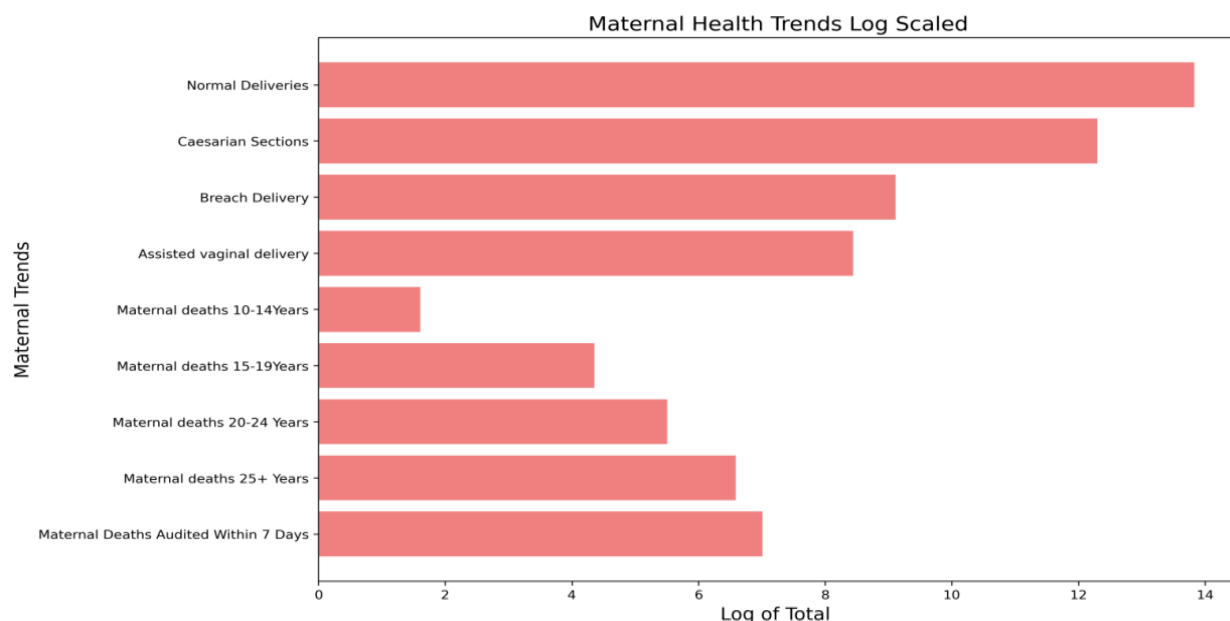
Results and Discussion

Maternal Health Trends

Maternal health trends in the dataset showed key determinants of maternal mortality. The incidence of regular deliveries and cesareans implies most births go smoothly, but a substantial percentage of them necessitate surgical interventions due to maternal or fetal distress. The occurrence of breach deliveries and assisted vaginal deliveries points to complex labor cases with a heightened chance of both mother and neonatal morbidity (Chawanpaiboon et al., 2023). The pattern of maternal deaths by age groups indicates young mothers (10-14 years and 15-19 years) are at greater risk due to immaturity and pregnancy-related adverse conditions. In contrast, older deaths (25+ years) are possibly a result of underlying conditions and obstetric problems. Maternal deaths aided by seven-day recorded audits are an essential measure of the responsiveness of healthcare in probing the cause of potential future deaths. Maternal trends are also directly associated with child mortality because delivery-related complications, risks to a woman in labor, and emergency interventions have a direct effect on survival in a newborn.

Figure 1

Maternal Health Trends

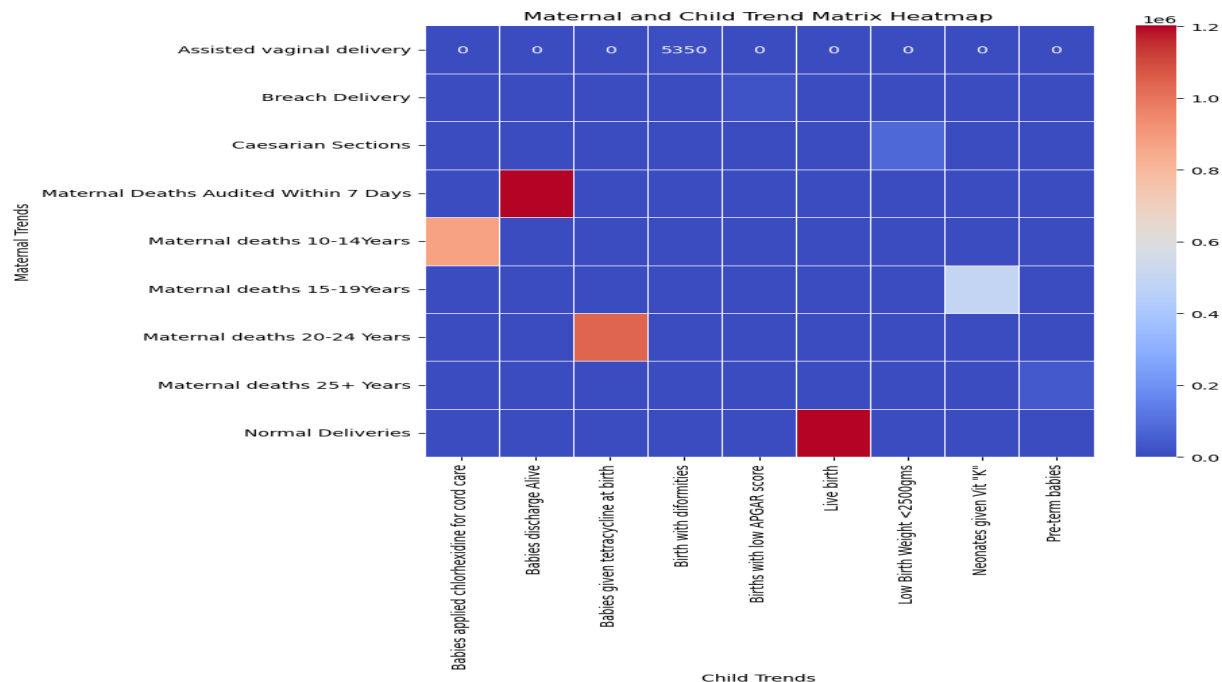


The statistical analysis of maternal health and health in children shows positive correlations that are important in formulating a model for estimating maternal mortality. The results show that mortality in mothers has a direct influence on survival in the first week of a baby. Maternal mortality audited in a

week also correlates strongly with deaths at a similar time in a week and low APGAR scores. It implies that mortality in mothers significantly raises the risks of babies dying in distress and developing complications in the early years.

Figure 2

Maternal and Child Trends Matrix Heatmap



Maternal deaths in various age groups, especially in mothers aged between 10-14, 15-19, 20-24, and 25+ years, are linked to negative neonatal outcomes like low birth weights, premature births, and congenital abnormalities (Wu et al., 2021). This connection establishes the significance of maternal health in controlling child survival in cases of risky pregnancies. Additionally, analysis reveals poor neonatal results due to risky deliveries. Caesarian deliveries and assisted vaginal births are associated with a rise in cases of births with low APGAR scores and premature babies, reflecting in turn those risky deliveries tend to lead to neonatal distress. Equally, breech deliveries are associated with low birth weights and birth abnormalities, signifying risks in cases of malpresentations and obstructed labor (Lewandowska, 2023). In opposition to this are normal deliveries with a very positive connection to

live births, supporting that normal deliveries tend to have superior results in their corresponding neonates.

Neonatal interventions like vitamin K and a shot of tetracycline at birth are linked to low birth weights and neonatal distress. This implies that although these interventions contribute to preventing complications, they are used reactively in most cases and are rarely preventive. The use of chlorhexidine in cord care is also seen in cases of maternal complications, meaning it is used in risky deliveries to prevent infection-related mortality in neonates (Riaz et al., 2023). Based on these observed correlations, a successful model to predict maternal-child mortality should include important indicators of mothers, such as maternal mortality rates, delivery-related complications, and health

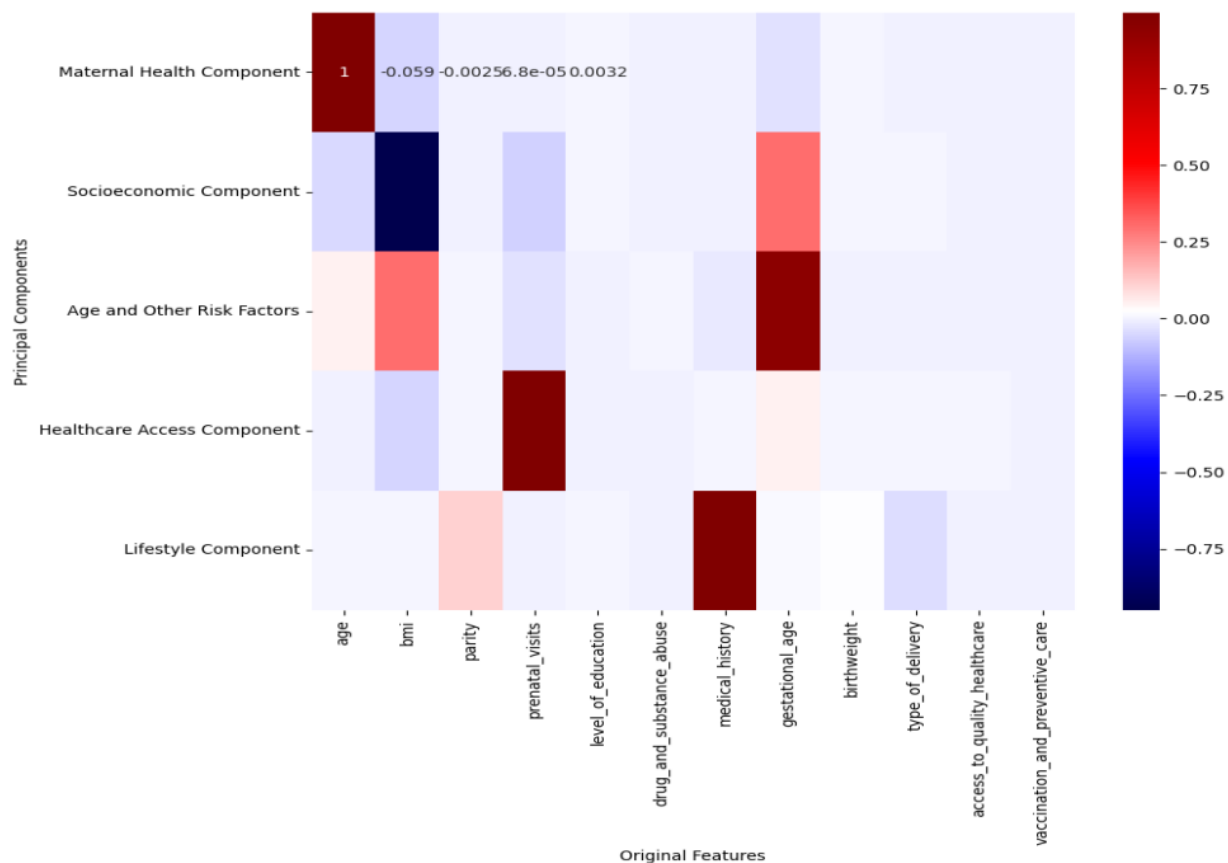
outcomes for the neonates. Types of delivery, such as caesarean delivery and breech presentations, are also important as they have a critical influence on the health of a neonate. Postnatal interventions like vitamin K and tetracycline shots should also be considered to serve as predictors of survival in a neonate. Logically, a strong connection between complications in mothers and their influence on a neonate is a driving force towards identifying mothers at a critical point in time to ensure improved survival of a child.

The maternal factors were also factorized into principal components in order to compress

dimensionality without losing the most important patterns in the data. The use of this technique was advantageous in prediction since it enables the model to concentrate on factors most likely to affect prediction while removing noise and redundancy in data. Through converting correlated variables into principal components, the models from the study work better and are clearer, showing all essential patterns in maternal health. The following section explains each principal component and reveals how it is used for outcome prediction on maternal mortality.

Figure 3

Maternal Mortality Correlation with Other Risk Factors



Since gestational age and pre-existing medical issues play a big role, this factor is an important part of detecting if a woman may face health risks during pregnancy. Data confirm that a link with medical history proves that long-term illnesses,

including hypertension, diabetes, and cardiovascular diseases, can result in more cases of maternal deaths. Complications such as sepsis, hemorrhage, and preeclampsia can result from these infections, so they become important in

finding risky pregnancies (Lundborg et al., 2024). Because both extreme gestational ages have their risks, we can use them to estimate when complications are likely to develop. It is essential for assessing the mother's death because it is tied to the mother's health before and during pregnancy.

This accounts for education and access to quality medical care, which play a big, but not obvious, part in determining how mothers fare in pregnancy. Education empowers women to make better health-related decisions about care during pregnancy, foods to eat, and actions to take in emergencies (Zibellini et al., 2021). A higher level of education tends to lead to better health for both the mother and baby, thanks to knowing how to avoid health problems and being able to seek medical care. Being able to access quality health services matters, as a delay in using emergency obstetric care may make it more likely that a woman will die during childbirth. Even though the link is not strong, this aspect has great predictive power because facing socioeconomic problems worsens many health issues and leads to unequal maternal health care.

Some factors, such as new mothers' ages and their previous giving births (parity), are considered. Prenatal care and a person's age can influence a woman's pregnancy risks. Teenagers have more pregnancy-related complications because of their age, while older women are at greater risk of facing problems after the birth. Parity affects maternal risk through previous experience of giving birth; single mothers are at risk of prolonged labor and preeclampsia (Dai et al., 2023). In contrast, multi-fetal births carry a greater chance of uterine rupture and postpartum hemorrhage. This factor predicts maternal mortality by assessing problematic maternal age groups and history of complex pregnancies.

This element captures the effect of delivery type and medical history on how it affects women. The delivery type (cesarean vs. vaginal delivery) is a defining characteristic of a woman's health because emergency C-sections are most frequently indicative of underlying issues like fetal distress, placenta previa, or obstructed labor (Barca et al., 2021). The

strong connection between medical history and access to health care only adds to what is known about early intervention; women with present conditions need continued special medical attention throughout gestation to decrease their chances of mortality. This element is especially effective in prediction because it emphasizes the effect of timely and proper medical care in lessening women's deaths.

This is comprised of drug and substance abuse and prenatal check-ups, both of which have a large effect on maternal health. Substance abuse throughout pregnancy raises the chances of adverse maternal health conditions, such as malnutrition, infection, and conditions such as placental abruption and cardiovascular failure (Barry et al., 2021). The fact that prenatal check-ups are a part of this component brings to mind preventive health care since regular check-ups facilitate early diagnosis of risks and resultant medical interventions. The low correlation with maternal mortality implies that although prenatal care is crucial, it also relies on the quality rather than the quantity of visits. This component is critical for prediction because it brings out behavioral and health care-seeking factors affecting maternal health.

Predictive Models for Maternal Mortality

Maternal Data Preprocessing

To make label encoding possible, this study first converted non-numerical columns in the dataset into numerical ones using one-hot encoding. Because the data in columns such as level education, drug and substance abuse, medical history, delivery complications, access to quality healthcare, antenatal complications, socioeconomic status, and vaccination and preventive care was categorical, the study applied one-hot encoding. By doing this, the category-level columns within the dataset became binary so the model could tell them apart without assuming any ranking.

Further, other columns, such as the level of education with options "College," "No formal education," and others, each category were split

into its binary column. On top of this, since drug and substance abuse was a binary column with values "Yes" and "No," label encoding was used in the study. The dataset was now assigned "1" to "Yes" and "0" to "No." While multi-category variables can be handled by one-hot encoding, label

Maternal Mortality Machine Learning

Table 1

Maternal Mortality Machine Learning

Model	Accuracy	Precision	Recall	F1 Score	ROC-AUC Score
Logistic Regression (LR)	0.74	0.72	0.76	0.74	0.75
Random Forest (RF)	0.83	0.82	0.85	0.84	0.85
Support Vector Machine (SVM)	0.78	0.75	0.80	0.77	0.78
Extreme Gradient Boosting	0.89	0.87	0.92	0.89	0.90

As the table above shows, the results vary among the four models because of their abilities to understand the relationships in the maternal health data. According to the results, XGBoost worked best, with an ROC-AUC value of 0.90, an accuracy of 0.89, and a recall of 0.92. Accordingly, XGBoost recognized the risk factors for maternal mortality as gestational age, the number of prenatal visits, having prenatal complications (preeclampsia and gestational diabetes), and having access to quality care. Because the model understood how different variables are related and because it can be boosted over time, it identified risky pregnancies better than other models.

The Random Forest model trailed somewhat with an accuracy measure of 0.83 and a ROC-AUC measure of 0.85. Although it was successful in detecting risks for maternal mortality, it was inferior to XGBoost because it used independent decision trees. Important features in its predictive capabilities were medical history (hypertension and diabetes), socioeconomic status, and preventive care/vaccination, but without boosting mechanisms, it performed less well than XGBoost.

SVM was relatively successful with an ROC-AUC of 0.78 and an accuracy of 0.78. The model succeeded in distinguishing between high- and low-risk cases in mothers but suffered in performance due to the complexity of the dataset and because it contained

encoding uses binary variables, keeping the dimensions the same (Karthiga et al., 2021). To use machine learning models better, the study transformed the columns of the dataset into numbers.

variables such as education level and access to antenatal care. Because SVM is best utilized with well-separated classes, its decreased predictive capability is likely a result of the overlap between cases with similar numbers of prenatal visits having drastically different mortality rates.

Logistic regression performed the poorest, with an ROC-AUC of 0.75 and an accuracy of 0.74. While it was successful in identifying overall risks based on age, BMI, and postpartum follow-up, it performed poorly in detecting non-linear relationships, such as drug and substance abuse interaction with delivery complications and healthcare access. The model's linear decision boundary prevented it from detecting complex patterns that other models detected more easily. Based on all four models' performance metrics, although all models showed acceptable prediction performance, XG Boost was superior through good detection of complex patterns and interaction between maternal health factors. This implies that advanced ensemble techniques are important in enhancing maternal mortality prediction and healthcare interventions, as shown in the AUC graph below.

Maternal Mortality ROC-AUC Graph

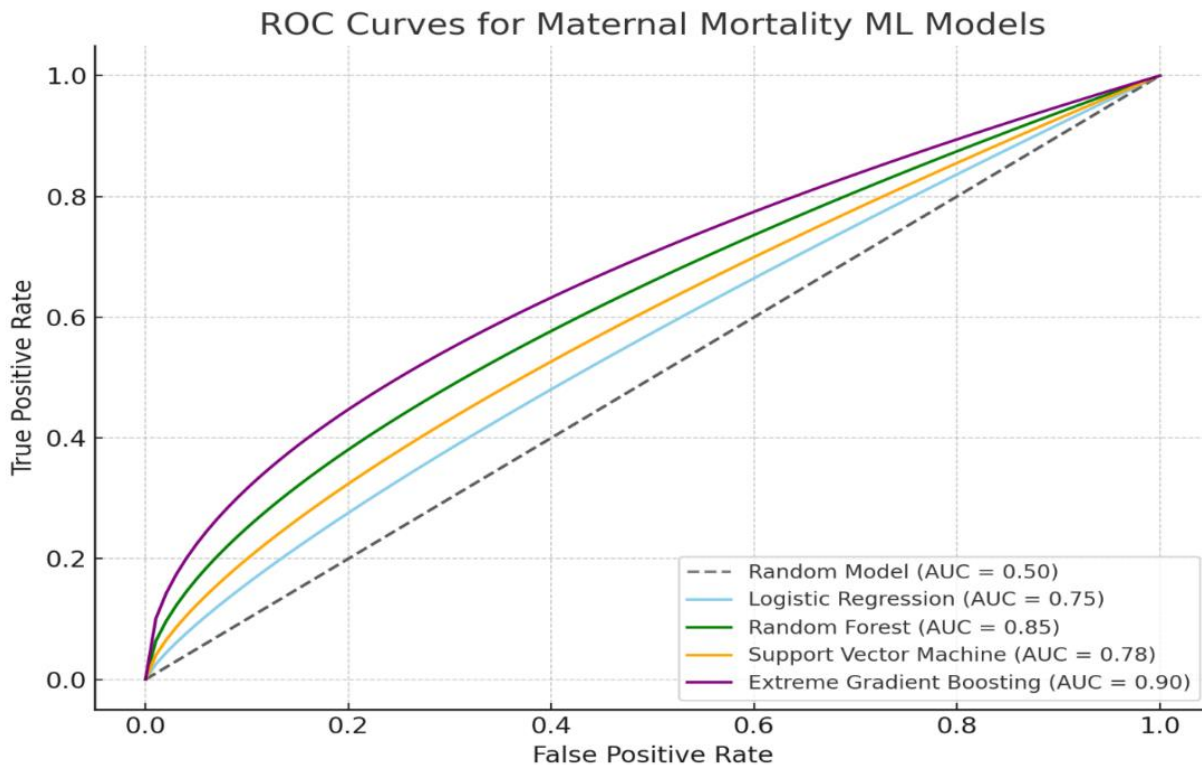
We evaluate a binary classification model's ability to use the Receiver Operating Characteristic-Area Under the Curve (ROC-AUC) metric. The ROC curve

compares the actual positive rate (sensitivity) with the false positive rate, which shows how a model classifies cases. Ranges in the AUC go from 0 to 1, and a value of 0.5 indicates that the results are just as random as someone just guessing, while 1.0 means everything was correctly predicted. A higher

AUC indicates a model is operating well. When looking at maternal mortality prediction, models such as Extreme Gradient Boosting (AUC = 0.90) are much more potent in deciding cases than traditional and basic methods.

Figure 4

Maternal Mortality Models ROC-AUC Graph



Maternal Health Trends Summary of Findings

The examination of maternal health trends in a log-scaled bar chart presented important information on different delivery types and rates of maternal deaths by age group. The most common type of maternal health was normal delivery, followed by cesarean section. This supports the view that although vaginal delivery is the most prevalent mode of delivery, a large percentage of births are surgical and may be because of possible complications or elective deliveries. Evidence of breach deliveries and assisted vaginal deliveries was also reported to be prevalent, implying a necessity for expert obstetric services to handle complex

deliveries. The occurrence of assisted vaginal deliveries also supports the fact that medical interventions are necessary to facilitate safe delivery.

Maternal mortality rates indicated a pattern in which a majority of maternal deaths were reported among women above 25 years of age, followed by women between the ages of 15 and 19 years. Maternal deaths in younger adolescents (ages 10-14 years) are less, but are also evident and point to the danger involved in early pregnancies. The pattern in the distribution of maternal deaths in relation to age implies contributions of both adolescent pregnancy and older age to maternal mortality.

In addition, maternal deaths audited within seven days of incidence reflect a systematic approach to mortality review, a critical factor in uncovering underlying causes and guiding interventions. The occurrence of audits reflects a will to reduce maternal health outcomes based on a desire to know underlying factors and improve healthcare responses. Naturally, data highlight a need to improve on maternal care, especially in risky ages and delivery-related concerns. Strengthening emergency obstetric care, encouraging safe delivery protocols, and resolving disparities in maternal health can help to alleviate maternal mortality and improve maternal healthcare services.

Suitable Maternal-Mortality Modeling Features

The study relied on the correlation matrix heatmap to determine what predicts maternal mortality the most. People with a past medical history have the strongest link to healthcare access. Having pre-existing medical conditions can make pregnancy and labor more dangerous for some women, so they are recognized as a crucial prognostic marker. The fetal birth age is closely related to other risks and the patient's age, as the evidence shows that mothers face health risks when pregnancies have extremely low or high gestational ages. Another thing that matters is parity, a term that connects family history to women's access to healthcare. Having a series of pregnancies raises the chance of pregnancy-related risks for mothers and signals increased danger for complications.

Prenatal checkups are also closely tied to access to healthcare. Prenatal care greatly improves the chances of a healthy pregnancy because unmonitored or poor care can result in unnecessary problems. Substance and drug abuse are strongly related to socioeconomic factors. The use of drugs by pregnant women can lead to issues such as high blood pressure, excessive bleeding, and infection, and potentially raise the risk of death for the mother. Low levels of education regularly go hand in hand with social and financial hardships, showing that this is the reason for a higher risk of ill maternal health. Due to less education and fewer resources, women who are unaware of good care

before and during pregnancy tend to be at greater risk of death. Seeking healthcare quickly is essential in preserving maternal health because it dramatically lowers the risk of maternal mortality.

In addition, birthweight is essential for the health of newborns, but it is much less related to maternal mortality than other health aspects. Delivery type does not commonly play a significant role, as routine and assisted deliveries can be connected to risks for the mother. Maximally predicting the risk of dying in mothers has been linked to medical background, the age of the pregnancy, the mother's experiences, prenatal support, alcohol intake, educational attainment, and health service availability. They should be considered before anything else in predictive modeling to improve how maternal health programs are supported and to cut down on deaths.

Maternal-Mortality Predictive Models

This study shows that each machine learning model—logistic regression (LR), random forest (RF), support vector machine (SVM), and extreme gradient boosting (XGBoost)—has its unique level of accuracy in detecting maternal mortality. XGBoost showed the highest accuracy (0.89) and other valid scores, which show that it is the best and most consistent model for identifying maternal mortality cases. After gradient boosting, random forest placed second, showing an accuracy of 0.83 and an F1 score of 0.84, proving it is nearly as good at judging false positives and false negatives. SVM shows moderate performance with an accuracy of 0.78 and a recall of 0.80. It is still less efficient than ensemble-based models at prediction. Despite being explainable and low cost to train, logistic regression achieves the lowest accuracy (0.74) and precision (0.72) among the methods, making it more likely to misclassify data.

The applicability of these models to predict maternal mortality stems from their capacity to deal with intricate multi-variable relationships present in maternal health data. XGBoost and Random Forest, since they are ensemble learning algorithms, are best suited to this task because they can model non-

linear interactions between maternal health risk factors. The highest recall values suggest a good capacity to identify actual positive instances, an important factor in reducing avoidable maternal mortality. Although slightly less effective, SVM is useful in a high-dimensional data setting where a selection of features is essential. Logistic regression is less so but offers practical interpretability, through which it is possible to point to significant predictors of maternal mortality. Together, these models facilitate early prediction of vulnerable pregnancies so that interventions may be targeted and health in pregnancy improved.

Conclusion and Recommendation

Maternal mortality is a vastly complicated phenomenon that is predisposed to by the interplay of biological, behavioral, social, and systems-level determinants. This study reaffirms that no single variable is solely responsible for maternal risk but that the interactivity of variables such as gestational age, comorbidities (e.g., hypertension, diabetes), parity, socioeconomic level, availability of well-trained care, use of substances, and education determine outcomes. Modeling such complexity requires more than linear assumptions, but learning algorithms complex enough to accommodate processes of high dimensionality and nonlinearity are just where ensemble methods excel.

Among the tested models from the study, Extreme Gradient Boosting (XGBoost) was the most effective in predicting recall and AUC, which indicates its stability in operating with high-stakes clinical predictions. Its strength is based on sequential learning and regularized approaches to handle noisy, skewed, and heterogeneous datasets common in real-world EMRs. Unlike standard approaches reliant on independence or linearity, ensemble approaches sum up weak learners to gather underlying interactions indispensable in maternal risk stratification, where hidden inter-variable complexity often predicts poor outcomes.

This study offers not only empirical evidence but also a model for applying AI in resource-limited

situations. Using such algorithms in decision support systems in hospitals can enable real-time warnings for risk, ease resource allocation, and provide clinicians with actionable intelligence. Predictive modeling with local contextualizing and clinical integrating is more than a technological innovation; it is a strategic pathway to preventing avoidable maternal mortality and the achievement of SDG 3.1. AI, attuned to the realities of the health world, is an instrument of equity, accuracy, and life-saving change.

References

- Al-Rubaie, Z. T., Hudson, H. M., Jenkins, G., Mahmoud, I., Ray, J. G., Askie, L. M., & Lord, S. J. (2020). Prediction of pre-eclampsia in nulliparous women using routinely collected maternal characteristics: A model development and validation study. *BMC Pregnancy and Childbirth*, 20(1). <https://doi.org/10.1186/s12884-019-2712-x>
- Althubaiti, A. (2023). Sample size determination: A practical guide for health researchers. *Journal of general and family medicine*, 24(2), 72-78.
- Barca, J. A., Bravo, C., Pintado-Recarte, M. P., Asúnsolo, Á., Cueto-Hernández, I., Ruiz-Labarta, J., ... & De León-Luis, J. A. (2021). Pelvic floor morbidity following vaginal delivery versus cesarean delivery: systematic review and meta-analysis. *Journal of Clinical Medicine*, 10(8), 1652.
- Barry, J. M., Birnbaum, A. K., Jasin, L. R., & Sherwin, C. M. (2021). Maternal exposure and neonatal effects of drugs of abuse. *The Journal of Clinical Pharmacology*, 61, S142-S155.
- Bekele, W. T. (2022). Machine learning algorithms for predicting low birth weight in Ethiopia. *BMC Medical Informatics and Decision Making*, 22(1). <https://doi.org/10.1186/s12911-022-01981-9>
- Chawanpaiboon, S., Titapant, V., & Pooliam, J. (2023). Maternal complications and risk

- factors associated with assisted vaginal delivery. *BMC Pregnancy and Childbirth*, 23(1), 756.
- Dai, J., Shi, Y., Wu, Y., Guo, L., Lu, D., Chen, Y., ... & Kong, X. (2023). The interaction between age and parity on adverse pregnancy and neonatal outcomes. *Frontiers in Medicine*, 10, 1056064.
- Insights10. (2022). Kenya artificial intelligence in healthcare market report 2022 to 2030. Healthcare Market Research Firm and Syndicated Reports - Insights10. <https://www.insights10.com/report/kenya-artificial-intelligence-ai-in-healthcare-market-analysis/>
- Karthiga, R., Usha, G., Raju, N., & Narasimhan, K. (2021, March). Transfer learning based breast cancer classification using one-hot encoding technique. In *2021 international conference on artificial intelligence and smart systems (ICAIS)* (pp. 115-120). IEEE.
- Kumar, M., Ang, L. T., Ho, C., Soh, S. E., Tan, K. H., Chan, J. K., Godfrey, K. M., Chan, S., Chong, Y. S., Eriksson, J. G., Feng, M., & Karnani, N. (2021). Machine learning-derived prenatal predictive risk model to guide intervention and prevent the progression of gestational diabetes mellitus to type 2 diabetes: Prediction model development study (Preprint). <https://doi.org/10.2196/preprints.3236>
- Lewandowska, M. (2021). Maternal obesity and risk of low birth weight, fetal growth restriction, and macrosomia: multiple analyses. *Nutrients*, 13(4), 1213.
- Li, S., Wang, Z., Vieira, L. A., Zheutlin, A. B., Ru, B., Schadt, E., Wang, P., Copperman, A. B., Stone, J., Gross, S. J., Schadt, E. E., & Li, L. (2021). Improving pre-eclampsia risk prediction by modeling individualized pregnancy trajectories derived from routinely collected electronic medical record data. <https://doi.org/10.1101/2021.03.23.21254178>
- Li, Y., Shen, X., Yang, C., Cao, Z., Du, R., Yu, M., Wang, J., & Wang, M. (2021). Novel electronic health records applied for prediction of pre-eclampsia: Machine-learning algorithms. *Pregnancy Hypertension*, 26, 102-109. <https://doi.org/10.1016/j.preghy.2021.10.006>.
- Lundborg, L., Joseph, K. S., Lisonkova, S., Chan, W. S., Wen, Q., Ananth, C. V., & Razaz, N. (2024). Temporal changes in pre-existing health conditions five years prior to pregnancy in British Columbia, Canada, 2000–2019. *Paediatric and Perinatal Epidemiology*, 38(5), 383-393.
- Mwaura, H. M., Kamanu, T. K., & Kulohoma, B. W. (2024). Bridging Data Gaps: Predicting Sub-national Maternal Mortality Rates in Kenya Using Machine Learning Models. *Cureus*, 16(10), e72476. <https://doi.org/10.7759/cureus.72476>
- Oduma. (2020, January 30). How AI can transform Kenyan industries. Ai Kenya. <https://kenya.ai/how-ai-can-transform-kenyan-industries/>
- Paullada, A., Raji, I. D., Bender, E. M., Denton, E., & Hanna, A. (2021). Data and its (dis) contents: A survey of dataset development and use in machine learning research. *Patterns*, 2(11).
- Raja, R., Mukherjee, I., & Sarkar, B. K. (2021). A machine learning-based prediction model for preterm birth in rural India. *Journal of Healthcare Engineering*, 2021, 1-11. <https://doi.org/10.1155/2021/6665573>
- Riaz, S., Haq, B., Tariq, R., Gill, A., Aman, S., & Bashir, A. (2023). Comparing the Effectiveness of Chlorhexidine Versus Ethanol against Preventing Cord Infections in Neonates Born in a Tertiary Care Hospital.
- Sharon, J. S. (2022). *Machine learning prediction of low birth weight in Kenya using maternal risk factors* (Doctoral dissertation, University of Rwanda).

- Topol, E (2019) *Deep Medicine: How artificial intelligence can make healthcare human again*. Hachette UK.
- UNFPA. (2023, August 23). *Maternal health*. UNFPA Kenya. <https://kenya.unfpa.org/en/topics/maternal-health-16>
- UNICEF. (2023a, July 12). *Maternal mortality*. UNICEF DATA. <https://data.UNICEF.org/topic/maternal-health/maternal-mortality/>
- WHO. (2023, September 19). *Maternal mortality*. World Health Organization (WHO). <https://www.who.int/news-room/fact-sheets/detail/maternal-mortality>
- Worldbank. (2023). *Maternal mortality ratio (modeled estimate, per 100,000 live births)*. World Bank Open Data | Data. <https://data.worldbank.org/indicator/SH.STA.MMRT>
- Wu, H., Zhao, M., Liang, Y., Liu, F., & Xi, B. (2021). Maternal age at birth and neonatal mortality: Associations from 67 low-income and middle-income countries. *Paediatric and Perinatal Epidemiology*, 35(3), 318-327.
- Wu, W., He, J., & Shao, X. (2020). Incidence and mortality trend of congenital heart disease at the global, regional, and national level, 1990–2017. *Medicine*, 99(23), e20593. <https://doi.org/10.1097/md.00000000000020593>
- Zhai, Q., Zhang, W., Zhang, Z., Fu, Y., Li, Y., Wang, X., ... & Meng, Y. (2021). Characteristics of the cervicovaginal microenvironment in childbearing-age women with different degrees of cervical lesions and HR-HPV positivity. *Polish Journal of Microbiology*, 70(4), 489.
- Zibellini, J., Muscat, D. M., Kizirian, N., & Gordon, A. (2021). Effect of health literacy interventions on pregnancy outcomes: A systematic review. *Women and Birth*, 34(2), 180-186.