Pregnancy Outcomes in facility deliveries in Kenya and Uganda

***Abstract*— Maternity registers offer a viable approach of tracking pregnancy outcomes and recognizing prospects for perinatal death prevention as the number of facility-based deliveries rises around the world. By defining facility-based pregnancy outcomes in Kenya and Uganda, this paper hopes to contribute to global quality improvement initiatives. To better understand and predict pregnancy outcomes, machine learning approaches have been used. Class imbalance in datasets is a serious problem that can cause pregnancy outcome predictions to be biased towards the majority class, lowering the dependability of machine learning models. Given the hazards, a reduction in memory can have life-threatening repercussions for both the mother and the infant. The dataset was subjected to a cost-sensitive learning and synthetic minority oversampling technique (SMOTE) in order to address this issue. This paper seeks to contribute to worldwide quality improvement and mortality prevention efforts by characterizing facility-based pregnancy outcomes for live born infants utilizing improved maternity register data. The data was preprocessed, and a variety of machine learning classification techniques (such as ZeroR, Decision Tree, and KNN, Random Forest) were used.**

Keywords—classification; feature selection; imbalanced dataset; machine learning

I. Introduction

While maternal mortality reduced by 44% globally between 1990 and 2015, low-income regions continue to bear a significant mortality burden [1]. Each year, an estimated 2.6 million third-trimester stillbirths occur globally [3], more than tripling the mortality associated with healthy pregnancies. Stillbirths have been called the "unfinished agenda" of the Millennium Development Goals, and the WHO's Every Newborn Action Plan outlines a plan to eliminate preventable newborn deaths and stillbirths by 2035 [4]. Counting every birth and its outcome is one of the plan's strategic objectives [4]. Strengthening regular health systems data, such as maternity ward birth registers, offers a promising opportunity for more thoroughly and reliably enumerating pregnancy outcomes and identifying opportunities for perinatal death prevention as facility-based deliveries increase [5][14].

Given the enormous burden of mortality in the region, Sub-Saharan Africa is a particular focus[14]. Estimates of maternal mortality remain high, at 546 per 100,000 live births [1] and 28.7 per 1000 total births [3]. Despite the fact that these numbers show significant progress in tracking pregnancy outcomes, underestimating remains a significant obstacle to reducing perinatal mortality. [10].

Lack of sufficient registration systems[journal] is a major contributor to underestimate. Only South Africa had a sufficient register system, according to the Lancet study on civil registration and vital statistics, which concluded that of the Sub-Saharan African countries with civil registration and vital statistics data available between 2005 and 2012, only South Africa did [6]. Other obstacles in properly counting pregnancy outcomes include estimations of gestational age, which vary in accuracy depending on the kind and timing of pregnancy dating (last reported menstrual period, ultrasound evaluation, size-based estimates) [7, 8].

Furthermore, the literature's uneven definition of stillbirth, with lower gestational age limits ranging from 18–28 weeks [2], further muddles classification and international comparisons. Nonetheless, the number of deaths that may have been avoided is significant. [14].

Approximately half of all stillbirths occur during the intrapartum period [3], when prophylaxis is most effective.

Based on facility deliveries in Kenya and Uganda, we give a prediction of pregnancy outcomes using machine learning approaches in this research. The dataset, which contains anonymized patient level delivery data from maternity registers that were recorded monthly, is publicly available in Dryad from 23 health facilities, including 17 in Migori county in western Kenya and six in Busoga area in eastern Uganda. The paper is unique in that it uses machine learning techniques (namely classification) to predict pregnancy outcomes. A methodology like this could be used to better understand pregnancy patterns and reduce perinatal mortality.

The remainder of the paper is structured as follows: A critical literature review was carried out in section 2. This is a continuation of our research methodology from Section 3. Section 4 presents the experimental results. Finally, in section 5, the highlights of the obtained results are presented.

II. Background

Using the dataset, many researchers have conducted experiments to detect pregnancy outcomes.
Phelgona Otieno, For example, a pair-matched, cluster randomized controlled trial across 20 facilities in Eastern Uganda and Western Kenya described the study protocol for implementing and evaluating a package of facility-based interventions to improve care during this critical window. [14]

Sobhy and colleagues validated critical data on maternal and perinatal mortality associated with cesarean delivery (CD) in low- and middle-income countries (LMICs). This study, which was designed to be and colleagues a nearly comprehensive meta-analysis of all studies published since 2000, provided an important benchmark from which to measure progress in improving maternal and neonatal health. [39].

At the historic Millennium Summit in September 2000, world leaders agreed to adopt the Millennium Development Goals (MDGs) with the goal of improving the lives of the world's poor, primarily aiming to quantify maternal mortality worldwide by underlying cause and age from 1990 to 2015[1]. One of the goals, MDG 5, aimed for a 75% reduction in global maternal mortality over the next 25 years. Based on the data obtained for MDG 5, we projected the levels and trends in maternal mortality for 183 countries from 2016 to 2030. [1]

In a separate study, James P Neilson1 evaluated the efficacy, safety, and acceptability of any medical treatment for early pregnancy failure (anembryonic pregnancies or embryonic and fetal deaths before 24 weeks). Randomized trials comparing medical treatment with another treatment (e.g., surgical evacuation), or placebo, or no treatment for early pregnancy failure were excluded, as were quasi-random studies.

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III. Research work

The factors affecting pregnancy outcomes in facility deliveries in Kenya and Uganda are investigated in this paper. Maternity registers are an important source of information for determining pregnancy outcomes, particularly for mothers and infants at high risk of perinatal mortality. [journal] that has been saved in the database. The dataset was published on dryad on August 21, 2020.:

A. Dataset

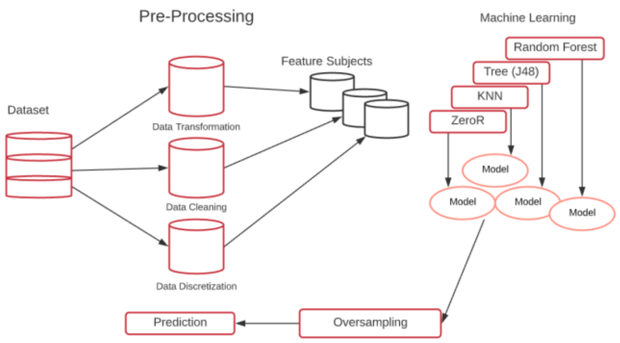
There are 61018 instances in the dataset, each with 22 attributes. It becomes 61018 instances with 13 attributes after preprocessing and removing the unnecessary attributes. Cross-sectional data were collected over an 18-month period from previously strengthened maternity registers at 23 facilities for this dataset.

Attribute	Description
Country	Differentiate by country
Facility_coded	Differentiate by facility
Referral_in	Describes if mother was referred into the hospital from another hospital (e.g Awendo to Migori County Referred Hospital)
Sex	Sex of baby
multiple	Indicates if mother delivered more than one baby
bba	Record contains designation that baby was born before arrival at the facility
doc_abortion	Record contains documentation that the pregnancy outcome was a spontneous abortion
doc_iufd	Record conains designation that the fetal outcome was intrauterine fetal demise
mother’s_age_cat	Designates whether record was considered a birth or not
c_cat_ga	Categorical GA groups
c_cat_bw	Categorical BW groups
c_birth_weight_g2	Birthweight in grams
c_birth_outcome	Describes whether the baby is born alive or still birth

The dataset includes information on the country, health facility code, sex, abortion documentation, and intrauterine fetal demise documentation. The details of the attributes recorded in the dataset are shown in Table I. Several features in the dataset, such as the mother's age category, gestational age category, and birth weight, have been found to be reliable in predicting pregnancy outcome. For this dataset, traditional machine learning techniques can predict with high accuracy. With a stratified class attribute distribution, we divided the dataset into training and test sets in an 80-20 ratio.

B. Research Methodology

Our main goal is to create a model that can predict birth outcomes and contribute to global quality improvement and mortality prevention efforts by predicting facility-based pregnancy outcomes for live born infants. The raw data is first preprocessed into a format that can be used by machine learning algorithms. Several tasks were completed during the preprocessing phase, including the removal of unnecessary columns and the transformation of categorical data into numeric values. When the dataset is ready to be trained after the pre-processing phase, four machine learning algorithms are applied to the dataset to predict the birth outcome.



C. Preprocessing of Predictor Attributes

To convert raw data into a format suitable for data mining tasks, preprocessing is required. Instead of null values, missing data in the dataset was replaced with the phrase "missing." We removed ID, Apgar Score1, Apgar Score5, Baby Discharge Status, Record Type, Mother's Status, Quarter, Mode of Delivery, and Baby Status from this dataset because they were unrelated to the birth outcome prediction. Because categorical values cause problems when applying machine learning algorithms, categorical attributes were converted to numeric values. Imputation, random sampling, and the creation of a new category were used to replace missing entries of documented IUFD, Birth weight, and Referred. The most frequent value was used to replace multiple, gender, categorical gestational age, and categorical birthweight.

D. Class Imbalance

The dataset was initially unbalanced, as evidenced by the fact that the values 'Born Alive' and 'Still Birth' accounted for roughly 93 percent and 7% of the total dataset, respectively, in the class attribute. To solve this problem, we used an oversampling technique, followed by hyperparameter tuning to improve the model's accuracy.

E. Feature Selection

In machine learning tasks, the selection of prominent features is critical for two reasons: (1) Irrelevant attributes act as noise, which can reduce the model's predictability. The model's predictability is improved by removing irrelevant attributes. (2) It causes the dataset's dimension to be reduced, allowing the curse of dimensionality to be avoided. The prominent features that can be used to predict the class attribute were found using the Pearson's Correlation, a well-known feature selection technique.

IV. CLASSIFIERS USED

To detect birth outcomes, Dataset was subjected to supervised classification algorithms. Four classification algorithms were used in this study. Prior to selecting attributes, we used classification algorithms and got different results for four of them. Following that, we used classification algorithms with a stratified train test split to improve our results.

A. ZeroR

ZeroR is the most basic classification method, relying solely on the target and disregarding all predictors. Because it only predicts the majority class for each query input, the ZeroR classifier has no predictability power. The ZeroR classifier, on the other hand, has been chosen as a baseline classifier. We achieved 92 percent accuracy for both the train and test sets after using the zeroR classifier.

B. Decision Tree

A decision tree is a machine learning algorithm that creates a tree structure from root to leaf, with each node making a decision based on an if/else condition. After optimizing hyperparameters, It was observed that the tree performs best at depth = 100 on this particular dataset. Using hyperparameter optimization and oversampling techniques, we were able to achieve 97 percent and 93 percent accuracy for the train and test sets, respectively.

C. K-Nearest Neighbour

The K-nearest neighbor (KNN) algorithm is a machine learning algorithm used to solve classification problems. The KNN calculates the distance between each query data point and all other training data points. Following that, the query data-K point's nearest neighbors are selected. Following the identification of the neighbors, the algorithm conducts a simple voting among the neighbors, with the majority class being labeled as the predicted class. The distances between the query data point and the training data points are measured using the Euclidean distance (equation 4) metric. After applying KNN, we obtained 93% and 90% on train and test set respectively.

D. Random Forest

Random forests, also known as random decision forests, are an ensemble learning method for classification, regression, and other tasks that works by training a large number of decision trees. For classification tasks, the random forest's output is the class chosen by the majority of trees. The mean or average prediction of the individual trees is returned for regression tasks. Random decision forests address the problem of decision trees overfitting their training set. After applying Random Forest with oversampling and hyperparameter tuning , we were able to obtain 96% accuracy in train and 93% accuracy in test set.

V. Results and Discussion

Algorithm	Accuracy	Precision	Recall	F-measure
ZeroR	0.92	0.86	0.93	0.89
Decision Tree	0.92	0.92	0.69	0.76
KNN	0.93	0.96	0.94	0.94
Random Forest	0.96	0.97	0.97	0.97

Fig1: Evaluation on Training Set

Algorithm	Accuracy	Precision	Recall	F-measure
ZeroR	0.92	0.86	0.93	0.89
Decision Tree	0.94	0.95	0.95	0.95
KNN	0.90	0.94	0.91	0.92
Random Forest	0.96	0.96	0.96	0.96

Fig2: Evaluation on Test Set

The comparision between accuracy, precision, recall and f-measure of the four classification algorithms is showed in fig1 and fig2 respectively.

Experimental Results from fig1 and fig2 indicate for the training set an accuracy of 96% is obtained using the Random Forest Classifier with oversampling which is the highest accuracy that we have achieved in this experiment.

For the test set, it is observed that 94% accuracy is obtained using the Decision Tree which is the highest and 90% accuracy is achieved by applying K-nearest neighbour algorithm which is the lowest among all the test accuracies.

VI.Conclusion

There is a significant unsolved burden of fetal death among facility-based deliveries in Kenya and Uganda. Premature and low-birth-weight babies, as well as pregnancies requiring emergency intrapartum care, are among the most vulnerable. Documenting all pregnancy outcomes, including pregnancy loss before 28 weeks, is a critical first step toward emphasizing the need for better care for the most vulnerable infants and pregnancies. Maternity registers are a valuable data source as the number of facility-based deliveries rises, especially when data quality is prioritized and efforts are made to ensure that every pregnancy is counted.[14].

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