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Original Article

Parametric Versus Non-Parametric Models for Predicting Infant Mortality within Communities in Uganda using the 2016 Uganda Demographic and Health Survey Data

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ABSTRACT

Machine learning techniques have been infrequently used to identify community-based infant mortality risks. Achieving SDG 3 Targets 3.2 and 3.3 could be expedited by early detection of at-risk infants within communities. This study aimed to devise a community-centric algorithm for predicting infant mortality. We analysed UDHS 2016 data containing birth records for 22,635 children born within the five years preceding the survey, excluding those born within a year of the interview date. Twelve machine learning models were evaluated for their predictive capabilities using the area under the receiver operating characteristic curve (AUC ROC) in Python. Data subsets were divided into training and testing sets in a 2:1 ratio. Among the evaluated models, CatBoost showed superior performance with an AUC ROC of 74.9%. The five most influential variables for the CatBoost model were postnatal care utilisation, paternal age, household size, preceding birth interval, and maternal age. While the algorithm's best performance was achieved using 28 variables, it still exhibited robust predictive power when limited to the top 8 or 10 variables. Hence, CatBoost stands out as an effective tool for identifying community-based infant mortality risks.

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INTRODUCTION

Every year, more than 8 million children die before reaching their fifth birthday. The majority of these deaths occur in developing countries and are caused by diseases that are either preventable or treatable (Oestergaard et al., 2011). Countries have shown certain advancements in diminishing child mortality, witnessing rapid reductions in recent times. However, these improvements remain inadequate to fulfil the requirements of SDG3's Targets 3.2 and 3.3. Notably, strides towards reducing neonatal and infant fatalities have been rather modest, as they presently contribute to a larger proportion of global child mortalities compared to the 1990s. Newborn deaths presently constitute nearly 31% of all fatalities among children below the age of five. Major contributors to infant mortality include issues such as pre-term births, respiratory difficulties during or post-delivery, as well as infections affecting the bloodstream and lungs (Oestergaard et al., 2011). Attaining the 3rd Sustainable Development Goal necessitates the creation of dependable models capable of forecasting infant and childhood mortality within communities. Additionally, it is advised that further research explore the validation and impact of current models, extending to predicting mortality among newborns (Medlock et al., 2011).

Other studies have used machine learning models for predicting neonatal mortality and demonstrated that machine learning can accurately predict death in neonates. Similarly, Sheikhtaheri et al. (2021a) employed several machine learning models, including an Artificial Neural Network, a decision tree, a Random Forest, C5.0, a CHART tree, a Support Vector Machine, a Bayesian network, and an ensemble model to improve physicians' ability to predict neonatal deaths. Batista et al. (2021) used different machine learning algorithms to predict the risk of neonatal mortality using only data routinely available from birth records in the municipality of São Paulo, Brazil. Results indicated that machine learning algorithms were able to identify, with very high predictive power, the neonatal mortality risk of newborns using only these routinely collected data.

In order to predict neonatal mortality at various points during hospitalisation, Sun et al. (2021) used two different predictive models, one a deep learning long-short-term memory (LSTM) model and the other a logistic regression model (LRM). Based on the findings, existing neonatal disease severity scores were outperformed by the LRM and LSTM predictive models of neonatal death using the high-definition phenotype.

In Tanzania, the application of the Generalized Linear Model (GLM) was employed to formulate practical tools for prognosticating neonatal mortality within the Neonatal Intensive Care Unit. The research aimed to determine a tool that strikes a balance between precision and user-friendliness within a resource-constrained clinical environment. By contrasting the most suitable GLM with simplified iterations, the study identified the optimal contender: a three-variable GLM comprising temperature, heart rate, and birth weight (Kovacs et al., 2021). Based on parametric models, Gebremariam et al. (2021) utilised the multivariate logistic regression model to identify potential prognostic determinants for early neonatal mortality.

The potential for artificial intelligence-driven approaches extends to enhancing prenatal birth defect diagnosis and outcomes in assisted reproductive technology. While machine learning

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algorithms leveraging perinatal health indicators to anticipate conditions such as preterm birth, birth weight, preeclampsia, mortality, hypertensive disorders, and postpartum depression remain relatively unexplored, they hold promise. Notably, real-time electronic health recording and predictive modelling through artificial intelligence have demonstrated initial achievements in foetal monitoring and overseeing women with gestational diabetes, particularly in settings with limited resources (Ramakrishnan et al., 2021).

Likewise, Joseph and Oladokun (2022) delved into the impact of enhanced sanitation and access to safe drinking water on child well-being in West Africa. Their study employed a range of econometric methods, including fixed effects, dynamic ordinary least squares, panel fully modified least squares estimation approaches, and the Pedroni panel cointegration test. These analytical techniques collectively revealed a tangible reduction in under-five mortality rates due to advancements in water and sanitation facilities (Joseph and Oladokun, 2022). In an attempt to predict infant mortality, Joseph and Oladokun (2022) classified problems of infant mortality to determine whether an infant will survive until his/her first birthday, both as a binary and multi-class based on the time of death. Saravanou et al. (2021) showed experimental evaluation comparisons between different predictive models (including those used by epidemiologic researchers), various combinations of features, different distributions in the training set, and the importance of features (Saravanou et al., 2021). Clearly, no prior research has harnessed nationally representative data such as DHS to evaluate the predictive capabilities of both parametric and non-parametric models. Thus, the primary aim of this investigation was to utilise a range of parametric and non-parametric algorithms. This approach was employed to discern the most effective models for identifying infants in the community who are susceptible to mortality, utilising comprehensive nationwide representative data.

MATERIALS AND METHODS

Ethical Considerations

The paper used the 2016 UDHS dataset, which is available for the public at the DHS Program website: *https://dhsprogram.com/data/available-datasets.cfm*. Registration is required before accessing and downloading the data sets. The UGIR7HFL (Kids Record) was strictly used in accomplishing this investigation. The data were accessed with permission from the DHS Program. The Demographic and Health Surveys in Uganda were conducted in adherence to the World Health Organization's ethical and safety recommendations for research. Participation in the surveys was on a voluntary basis, and informed consent was obtained from the participants. In order to ensure confidentiality, participants' identifiers were not included in the datasets.

Data

A total of 22,635 observations and 33 variables were imported as a data frame after merging into Python for rigorous analysis. Duplicate entries were checked and removed. A binary outcome variable (infant deaths) was considered, and its distribution was cross-checked. The data were not balanced, with the majority of the target variable corresponding to infants that were alive. The distribution of the data entries belonging to the two target variable categories was explored using Panda's profiler to check for distribution and correlation between the different features. The data were checked for missing values, and entries with missing values for children who were alive were dropped, while entries for the missing values for children who were reported dead were imputed using corresponding values for infants reported dead. This was done so as to balance the data, which in turn allowed proper assessment of the target variables. Categorical variables were encoded using ordinal encoding for ordinal categories and dummy encoding for non-ordinal categories. Numerical variables were rescaled using the Minmax scaler to a range between 0 and 1 in order to place all variables on the same scale.

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Since the target variable was not balanced, with more entries corresponding to infants that were alive (0) than those that were dead (1), the data were balanced by down-sampling the majority target variable to match the minority target variable using the Random Under Sampler. The remaining data were made up of 12,747 entries, with 90.4% (11,524) corresponding to infants that were alive and 9.6% that had died.

Machine Learning Spot Checking

Multiple machine learning algorithms were used in spot-checking to discover which algorithms performed best given the data. The different machine learning algorithms such as logistic regression, linear discriminant analysis, K-nearest neighbours, random forest, decision trees, extra trees, Naïve Bayes, support vector machines, multi-layer perceptions, light gradient boost machines, hist gradient boosting classifiers, and CatBoost were trained and tested using k-fold cross-validation, where the data were split into multiple folds such that each fold was used as a testing set while the rest of the data was used as a training set. The algorithms were scored using the area under the receiver operating characteristic curve. CatBoost performed best at it and was selected for further parameter tuning.

Machine Learning Fine Tuning

The CatBoost classification algorithm was used as the final machine learning algorithm, given its performance. Since CatBoost can function without encoding categorical variables, the categorical variables were used as they were in the data set. In order to acquire entries from the majority target variable that were equivalent to entries from the minority target variable, the data were randomly selected into 20 subsets. Each subset was split into a training and testing set at a ratio of 2:1. The CatBoost algorithm was trained on each training set, tested on the corresponding testing set, and scored using accuracy, which was expressed as the proportion of correctly predicted outcomes out of all predicted outcomes using Mathew’s correlation coefficient, F1 score (A machine learning evaluation metric that assesses a model’s accuracy. It combines a model’s precision and recall scores), and area under the receiver operating characteristic curve. The subset that yielded the best scores was used to retrain and test the model, and the resultant CatBoost model was saved using the joblib, a Python library used to export a trained machine-learning model ready for deployment with only the best-performing variable. The performance of the CatBoost algorithm in predicting infant risks of death is presented in *Table 1*.

Table 1: Performance of CatBoost algorithm in predicting infant risk of death.

	Mean	std	Min	25%	50%	75%	Max
Accuracy	0.8105	0.0072	0.7983	0.8054	0.8106	0.8147	0.8255
Mathew’s correlation coefficient	0.6365	0.0172	0.6128	0.6244	0.6367	0.6458	0.6751
F1 score	0.8039	0.0064	0.7902	0.8004	0.8048	0.8074	0.8154
AUC ROC	0.8706	0.0094	0.8502	0.866	0.8712	0.877	0.8861

RESULTS

After balancing the data to ensure that the number of infants who died for each group was equal to the number of infants who were alive in the subsample data, the authors moved on and created the machine learning algorithms. The results of the 12 various models were examined based on AUC-ROC using the completed data (*Figure 1*). The outcomes of which were helpful in identifying the most effective model for further investigation. The best-performing algorithms were CatBoost (0.749), LGBM (0.734), hist gradient boosting classifier (0.731) and random forest (0.728). The CatBoost classification algorithm was selected for fine-tuning.

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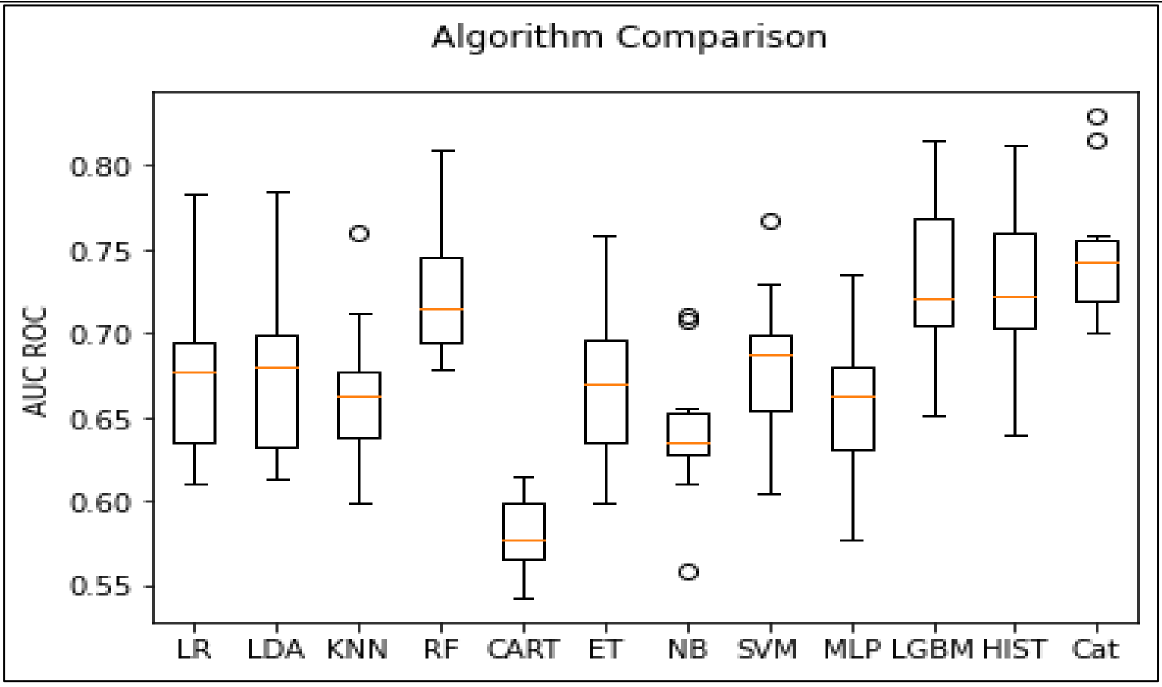
Figure 1: Comparison of classified machine learning algorithms based on AUC-ROC using balanced data



Key - LR: Logistic Regression, LDA: Linear Discriminant Analysis, KNN: K-nearest neighbours, RF: Random Forest, CART: Decision Trees, ET: Extra Trees, NB: Naïve Bayes, SVM: Support Vector Machines, MLP: Multi-Layer Perceptions, LGBM: Light Gradient Boost Machines, HIST: Hist Gradient Boosting Classifiers, Cat: CatBoost

Machine Learning Fine Tuning

Since the CatBoost classification algorithm can work with categorical variables that are not encoded, the unbalanced data were used without encoding the categorical variables. Entries corresponding to the majority outcome variable of infants that are alive were randomly sampled 20 times to match entries for the minority outcome variable of infants that died. Both outcome variables had 1,223 entries for each round of balancing. Each balanced iteration was split into a training and testing set at a ratio of 2:1. The CatBoost algorithm was trained and tested for each iteration and scored using accuracy, Mathew's correlation coefficient, the F1 score, and the area under the receiver operating curve.

The random sample that yielded the highest AUC ROC score was further examined using a confusion matrix and the area under the receiver operating curve. The confusion matrix revealed that the CatBoost algorithm has a significant false positive rate (N=120, 14.85%), mistaking infants who are still living for those who have passed away. Although the algorithm rarely predicted that infants who died were alive, it did have a low false negative rate (N=21, 2.60%). In that situation, the authors believed that it is appropriate to identify infants who are in danger in the community for quick referral and case management.

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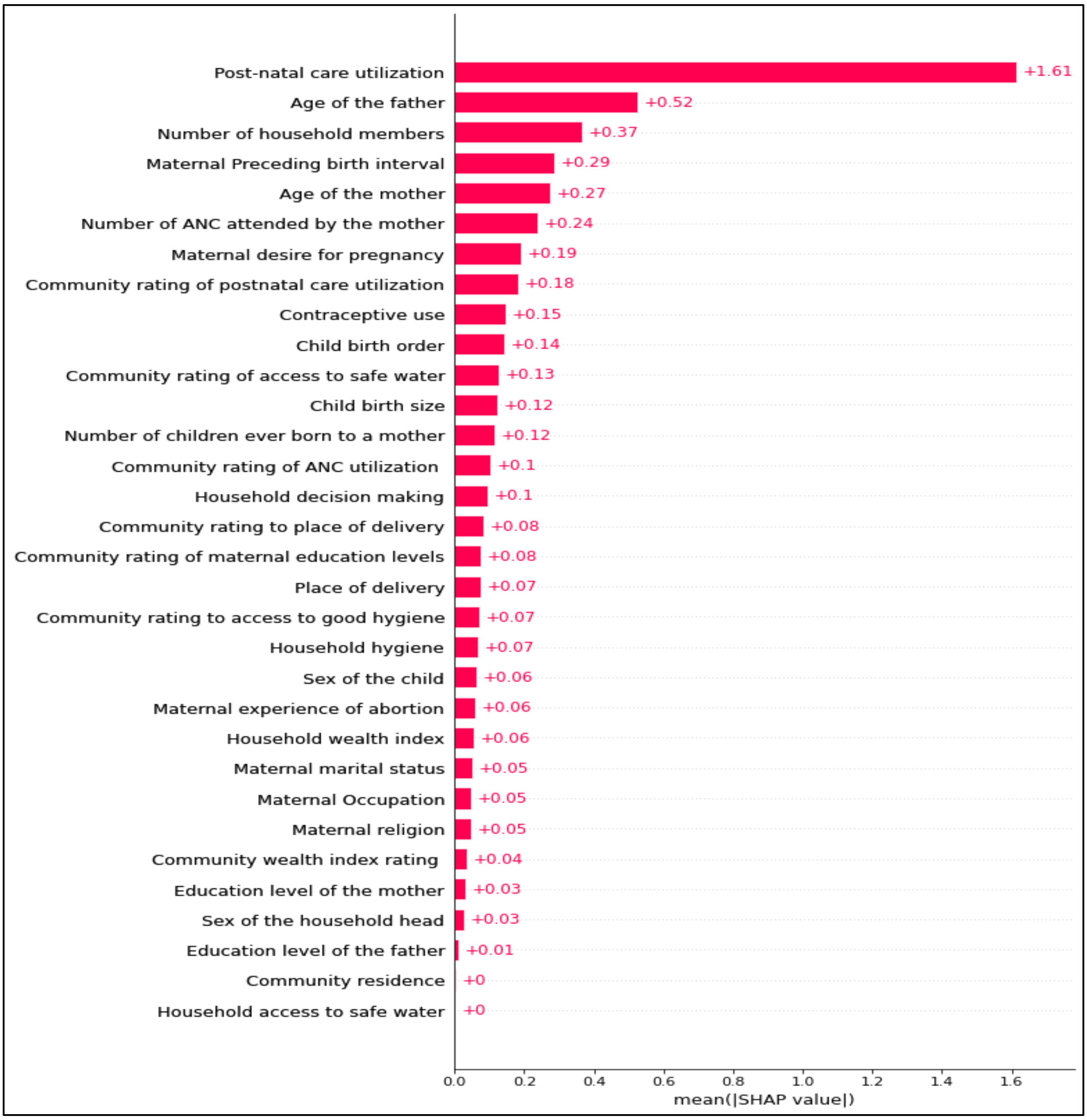
Figure 2: Ranking of variables by their contribution to predicting the likelihood of infant mortality in the community



From the area under the receiver operating characteristic curve, it was evident that the CatBoost algorithm performed far better than all the other computing algorithms. Of the 32 selected variables, the best five and the least five variables shown in Figure 2 have been summarised in *Table 2*.

The authors recognised the effect of unbalanced data in making predictions, which could result in skewed findings, leading to biased detection and referral. The missing data were filled using multiple imputations and averaged for quantitative accuracy to ensure completeness. The UDHS data indicated a relatively small proportion of infants who died, and as such, the data was balanced by randomly selecting the infants who survived. The results in Table 2 provide a detailed distribution of infants by selected study variables.

The top 5 predictive variables for the CatBoost algorithm were postnatal care utilisation (Alive: 96% received, Died: 39.9% received), age of the father (fathers older for infants that died (mean=35.12, median=35) than for those that are alive (mean=34.65, median=33) though not significantly), number of household members (more household members on average for infants

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that are alive (mean=5.98, median=5) than for those that died (mean=5.702, median=5)), maternal preceding birth interval (alive: 78.7% more than two years, died: 70.7% more than two years) and age of the mother (mothers younger for infants that died (mean=28.23, median=27) than for those that are alive (mean=28.48, median=28)). The least predictive variables included educational level of the mother (Alive: 77.1% primary and below, died: 85.1% primary and below), sex of the household head (Alive: 80.8% male, died: 78.4% male), educational level of the father (Alive: 63.9% primary and below, died: 65.5% primary and below), community residence (Alive: 78.9% rural, died: 82.1% rural) and least of all household access to safe water (Alive: 73.9% safe, Died: 63.9% safe). The trained CatBoost algorithm was saved using **joblib**. There was no difference when numerical variables were rescaled or not in the final algorithm.

Table 2: Description of selected variables in the balanced dataset for modelling

Best five variables	Alive		Died	
	Mean	**Median**	**Mean**	**Median**
PNC (%)	39.6		39.9	
Paternal age (Mean/Median)	34.65	33	35.12	35
Household size (Mean/Median)	5.98	5	5.7	5
Preceding birth Interval 2 years and above (%)	78.7		70.7	
Maternal age (Mean/Median)	28.48	28	28.23	27
Least five variables				
Maternal Education level (Primary and below) (%)	77.1		85.1	
Sex of the Household head (Male) (%)	80.8		78.4	
Paternal Education level (Primary and below) (%)	63.9		65.5	
Residence (Rural) (%)	78.9		82.1	
Access to safe water (%)	73.9		63.9	

Researchers usually find it difficult to narrow down the variables that should be selected from a large number of independent variables; if no statistically agreed approach is used, researchers end up overfitting the models, and hence multicollinearity. Finding a few factors that can adequately explain the majority of the data is necessary. Here, authors used the Python approach to rank the importance of the variables in predicting infants at risk of death in the community, whereas Variance Inflation Factors (VIF) were put into play to choose variables with VIF < 10 to be kept in the models. The authors examined the random contributions of the 28 variables that were chosen to the prediction of community newborns that would die.

This was carried up until a point where the performance of CatBoost could not be noticeably improved by the addition of further variables. The results of this performance are presented in *Figure 3*.

From this plot, the CatBoost algorithm performed best when 28 variables were used, followed by when 8 or 10 variables were used based on variable importance. The trained model using the streamlit Python library was deployed into a web application with the 28 top-performing variables. The app is accessible via the link: *https://bit.ly/3P8pjgg*.

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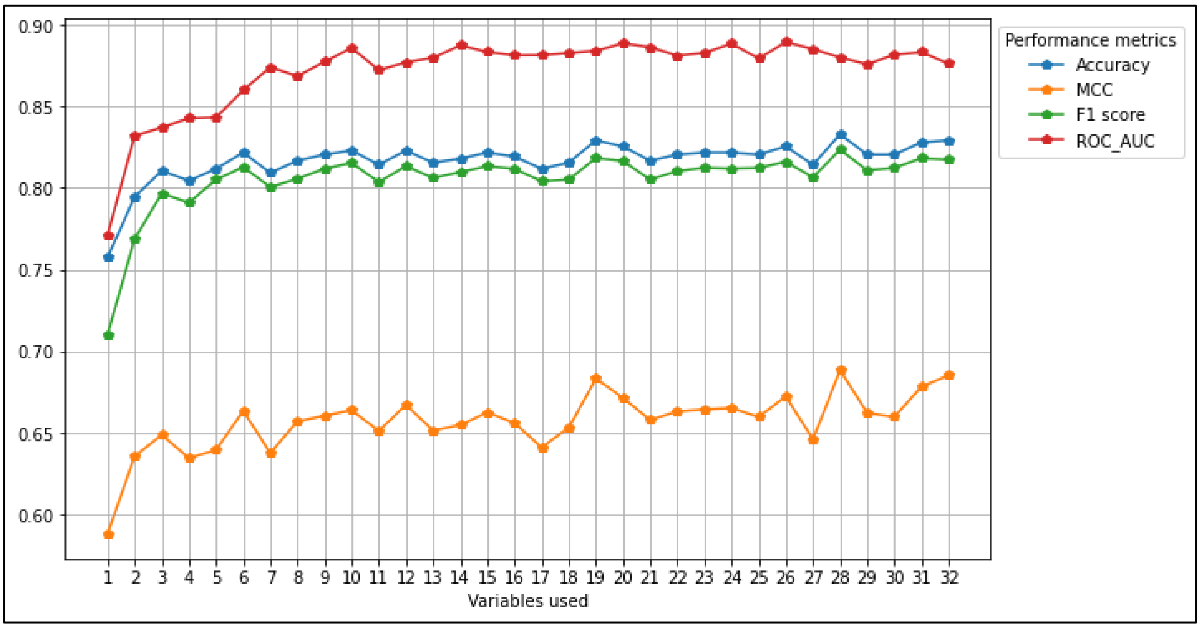
Figure 3: Performance of combinations of variables based on their variable importance



DISCUSSION

Recent research endeavours have undertaken comparative evaluations of prediction models, ultimately selecting a single model for prognosticating specific outcomes. For example, Mangold et al. (2021) employed a systematic review methodology to gauge the efficacy of machine learning models in forecasting infant mortality. Their findings highlighted the precision of machine learning models, particularly parametric ones, in predicting neonatal mortality. This accuracy arises from the fact that certain theoretically significant variables exhibit inconsistency across various models and specifications (Hegre & Sambanis, 2006). The persistent theoretical debates surrounding optimal causal models remain fundamental to the field (Muchlinski et al., 2016). These deliberations prompted scepticism about the logistic regression model's capability to predict infant and neonatal mortality (Emukule et al., 2014; Watson et al., 2014).

In a similar vein, Sheikhtaheri et al. (2021b) harnessed diverse machine learning models, including Artificial Neural Networks, decision trees, Random Forests, C5.0, CHART tree, Support Vector Machines, Bayesian networks, and an Ensemble Model to enhance physicians' neonatal death predictions within Neonatal Intensive Care Units. Their outcomes indicated the supportive role of machine learning models in improving such predictions.

To exhaust all potential model candidates, we engaged twelve classification machine learning algorithms for spot-checking using balanced data. This encompassed logistic regression, linear discriminant analysis, K-nearest neighbours, random forest, decision trees, extra trees, Naïve Bayes, Support Vector Machines, multi-layer perceptions, the light gradient boost machine, hist gradient boosting classifiers, and CatBoost. Based on our data, the highest mean AUC ROC values were 74.9%, 73.4%, 73.1%, 72.8%, and 0.728, corresponding to CatBoost, LGBM, hist gradient boosting classifier, random forest, and decision trees, respectively. Consequently, CatBoost was chosen for fine-tuning. The adoption of AUC ROC values for inter-model and inter-algorithm performance comparison followed the precedent of earlier researchers (Alaa et al., 2019; Darabi et al., 2019; Tiwari et al., 2022).

Numerous studies have also underscored the effectiveness of the CatBoost algorithm in prognosticating health-related outcomes. Its superiority over alternative algorithms was evident when applied to medical datasets (Hatami et al., 2022; Rois, 2022; Safaei-Farouji et al., 2022). Notably, our fine-tuned CatBoost

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algorithm exhibited its prowess in predicting neonatal mortality using diverse attributes. In terms of variable ranking, the foremost ten factors contributing to the prediction of infants at risk of mortality within communities encompassed postnatal care utilisation, paternal age, household size, preceding birth interval, maternal age, number of antenatal care visits, maternal desire for pregnancy, community assessment of postnatal care utilisation, contraceptive usage, and child birth order. Our findings align with prior studies that highlighted the association between these factors and infant mortality risks (Aheto, 2019; Crilly et al., 2021; Grunberg et al., 2019; Mboya et al., 2020).

While our model holds potential for identifying at-risk children within the Ugandan context, its applicability in developed countries necessitates adjustments due to the socioeconomic distinctions between these contexts. Furthermore, the model's assumptions rely on the constancy of all factors and the absence of unforeseen events or disasters.

CONCLUSION

While numerous studies have leveraged machine learning, a non-parametric methodology, to develop prediction models, there has been a limited focus on addressing community-centric health challenges rooted in community factors. Evidently, non-parametric models excel in predicting binary outcomes, often outperforming their parametric counterparts. Although the CatBoost algorithm showcased its proficiency in predicting infant outcomes, particularly fatalities, enhancing its efficacy might require the integration of more distinct features.

As expected, machine-learning-based non-parametric models emerged as scientifically superior in identifying community-based high-risk infants. An application grounded on the CatBoost algorithm could be readily developed for straightforward smartphone interfaces, empowering Village Health Teams to pinpoint and monitor high-risk infants. Such a proactive approach would pave the way for a significant reduction in infant mortality, particularly from avoidable causes, by ensuring timely detection, effective management, and prompt referral of vulnerable infant cases.

ABBREVIATIONS

UBOS: Uganda Bureau of Statistics; UDHS: Uganda Demographic and Health Survey; OR: Odds ratio; WHO: World Health Organization; UNICEF: United Nations Children Funds: IMR: Infant Mortality Rate; NMR: Neonatal Mortality Rate; PMTCT Prevention of Mother to Child Prevention SDG: Sustainable Development Goal: MDG: Millennium Development Goal; HIV/AIDS: Human Immune Virus/Acquired Immune Deficiency Syndrome; PSU: Primary Sampling Unit.

Acknowledgements

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Availability of Data and Materials

The DHS datasets are available for the public at the DHS program website: https://dhsprogram.com/data/available-datasets.cfm. Registration is required before accessing and downloading the data sets. The study used the UGKR7HFL and UGIR7HFL (Kid Record and Individual Recode –Women with completed interviews).

Authors' Contributions

BO: Participated in the conceptualisation of the study, took the lead in conducting the literature review, participated in writing the methodology, data processing and analysis, presentation of findings, discussion, and compiled the overall manuscript. **LA:** He guided the investigation and the formal analysis of data. **JO** guided the analysis processes and the review of the document.

Ethical Approval and Consent to Participate

This paper is based on secondary data that is available in the public domain. The data were accessed with permission from the DHS program. The Demographic and Health Surveys in Uganda

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were conducted in adherence to the World Health Organization's ethical and safety recommendations for research. Participation in the surveys was on a voluntary basis, and informed consent was obtained from the participants. In order to ensure confidentiality, participants' identifiers were not included in the datasets.

Competing Interests

The authors declare that they have no competing interests.

Consent for Publication

Not applicable

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