Sayeed *et al.*
Journal of Health, Population and Nutrition (2024) 43:170
https://doi.org/10.1186/s41043-024-00646-9

Journal of Health, Population and Nutrition

RESEARCH

Open Access

On the interpretability of the SVM model for predicting infant mortality in Bangladesh

Md Abu Sayeed[1*], Azizur Rahman[1], Atikur Rahman[1] and Rumana Rois[1*]

Abstract

Background Although machine learning (ML) models are well-liked for their outperformance in prediction, greatly avoided due to the lack of intuition and explanation of their predictions. Interpretable ML is, therefore, an emerging research field that combines the performance and interpretability of ML models to create comprehensive solutions for complex decision-making analysis. Conversely, infant mortality is a global public health concern affecting health, social well-being, socio-economic development, and healthcare services. The study employs advanced interpretable ML techniques to anticipate and understand the factors affecting infant mortality in Bangladesh, overcoming the shortcomings of the conventional logistic regression (LR) model.

Methods By utilizing the global surrogate model and local individual conditional expectation (ICE) interpretability technique, the interpretable support vector machine (SVM) has been used in this study to reveal significant characteristics of infant mortality using data from the Bangladesh Demographic and Health Survey (BDHS) 2017–18. To investigate intricate decision-making analysis of infant mortality, we adapted SVM and LR techniques with the hyperparameter tuning parameters. These models' performances were initially assessed using the receiver operating characteristics (ROC) curve, run-time, and confusion matrix parameters with 100 permutations. Afterward, the SVM model's model-agnostic explanation and the LR model's interpretation were compared to enhance advanced comprehension for further insights.

Results The results of the 100 permutations demonstrated that the LR model (Average: accuracy = 0.9105, precision = NaN, sensitivity = 0, specificity = 1, F1-score = 0, area under the ROC curve (AUC) = 0.6780, run-time = 0.0832) outperformed the SVM model (Average: accuracy = 0.8470, precision = 0.1062, sensitivity = 0.0949, specificity = 0.9209, F1-score = 0.1000, AUC = 0.5632, run-time = 0.0254) in predicting infant mortality, but the LR model had a slower run-time and it was unable to predict any positive cases. The interpretation of LR analysis revealed that infant mortality rates decrease when mothers give birth after over two years, with higher educational attainment, overweight or obese mothers, working mothers, and families with polluted cooking fuel having lower rates. The local ICE interpretability technique, which depicts individual influences on the average likelihood of dying within the first birthday, explores the interpretable SVM model that mothers with normal BMIs, giving birth within two years, using less polluted cooking fuel, working mothers, and having male infant were more likely to experience infant death. The interpretable SVM model based on the global surrogate model also reveals that working mothers who used polluted cooking fuel at home and working women who used less polluted cooking fuel but had a longer period between pregnancies than two years would have higher infant death rates. Even among non-working mothers who used polluted cooking fuel and gave birth within two years of the preceding one, infant death rates were higher.

*Correspondence:
Md Abu Sayeed
sayeed@juniv.edu; sayeed.stu2016@juniv.edu
Rumana Rois
rois@juniv.edu

Conclusions The interpretable SVM model reveals global interpretations help clinicians understand the entire conditional distribution, while local interpretations focus on specific instances, providing different insights into model behavior. Interpretable ML models aid policymakers, stakeholders, and families in understanding and preventing infant deaths by improving policy-making strategies and establishing effective family counseling services.

Keywords Individual conditional expectation, Interpretable machine learning models, Global surrogate models, Global interpretability techniques, Local interpretability techniques, Sigmoid kernel, Support vector classification

Introduction

Child mortality is a global public health concern affecting a nation's health, social well-being, socio-economic development, and primary healthcare services, making it a sensitive indicator of overall well-being [1–3]. Infant mortality, by definition, is the term used to describe deaths that occur within the first year of life [4]. Infant mortality is still a serious concern despite significant improvements in recent years. It has been reported that 2.3 million infants and 5 million children under five died in 2021 from preventable and curable causes [5–7]. Like many other developing nations, Bangladesh has experienced notable declines in both infant and child mortality during the past few decades [2, 8]. According to the 2017-18 Bangladesh Demographic Health Survey (BDHS) Report [3], there are about 38 deaths occur per 1,000 live births before the first birthday. Bangladesh has made remarkable progress in reducing infant mortality through transformative efforts. This drop has been largely attributed to the nation's targeted public health initiatives, emphasis on community-based interventions, and advancements in maternal education [9]. The ambitious third sustainable development goal (SDG), which aspires to reduce infant mortality rates to at least 12 deaths per 1000 live births, remains unachievable despite these significant advances in absolute numbers [10].

Understanding and predicting factors affecting infant mortality is crucial for achieving the SDG and ensuring a country's development and well-being. Numerous studies [2, 8, 11–17] looked into the possible factors and causes influencing infant mortality in Bangladesh. For instance, infant and child survival is significantly impacted by the birth interval [11, 15, 16]. Starting early maternal health care visits and regular intervals throughout pregnancy and postnatal periods [13]. Infant mortality rates are higher among mothers giving birth at home and lower-income groups [12, 14]. Factors such as antenatal care, wealth status, birth size, and child gender contribute to higher infant mortality rates [14]. Polluted or solid fuels also contribute to infant deaths in Bangladesh [15, 16]. Only three research articles [15–17] have employed machine learning (ML) algorithms to predict infant mortality in Bangladesh, despite the fact that the majority of studies examined infant mortality using a logistic regression (LR) model or estimated relative risk (RR). BDHS 2014 data was utilized by [17] to assess how well various ML models performed in predicting infant mortality in Bangladesh and discovered that the Support Vector Machine (SVM) model performed better. [15] and [16] evaluated the effectiveness of various ML models with simulation studies to forecast infant mortality in Bangladesh using data from the BDHS 2017–18. They then utilized a random forest (RF) model to interpret the model's results. Consequently, LR and RF models were applied to the BDHS 2017–18 data to interpret the results of the predicted infant mortality analysis. Utilizing data from the BDHS 2017–18, the SVM model has not previously been applied to understand and predict factors influencing infant mortality. We are therefore urged to use the SVM model for the BDHS 2017–18 data to understand and interpret the findings of the predicting infant mortality study.

SVM has been successfully applied to a variety of classification and regression problems; Support Vector Regression (SVR) handles regression problems, and Support Vector Classification (SVC) handles classification problems. We concentrate on SVC because it has proven effective in a range of classification problems, for instance, in bioinformatics [18, 19], in medical image analysis [20], in marketing research to classify customers choice [21], in medical studies to identify a common disease using straightforward clinical data [22], in predicting diabetes and coronary artery disease [23, 24], and in mortality prediction[25]. For infant mortality prediction, SVM provided 99% accuracy [26, 27], and even the BDHS 2014 data the SVM with Gaussian kernel model yielded 84% of accuracy with 97% of precision and 86% of sensitivity [17]. These studies, however, do not clarify how the results of the SVM models should be interpreted to predict infant mortality. Very few of the listed research have employed SVM for interpretation. [20] interpreted the medical image analysis output using a hybrid approach based on Quadtree decomposition, and [21] interpreted the marketing research output of classifying customer preferences using the local ICE interpretability techniques.

While several studies have shown that SVM features are strong at generalization, robustness, and preventing overfitting [28], one drawback of SVM is that it can be challenging to interpret the findings [29]. Furthermore, we noticed that [30] used two local interpretability techniques (Local Surrogate Models, Shapley Value) and five global interpretability techniques (Feature Importance, Partial Dependence Plot, Individual Conditional Expectation (ICE), Feature Interaction, Global Surrogate Models) to perfectly interpret the results of the RF model to predict hypertension. Very constructive interpretations of the RF outcomes were reported by [30] using global surrogate models, while very positive interpretations of the SVM outcomes were reported by [21] using the local ICE interpretability technique. Thus, the goal of this research is to predict infant mortality and use global surrogate models and local ICE interpretability techniques to interpret the SVM model's results.

Materials and methods

Data and variables

This study used secondary data extracted from the Bangladesh Demographic and Health Survey (BDHS), 2017–2018 [3]. The survey's data were gathered using a two-stage stratified random sampling design; further details can be found at https://dhsprogram.com/data/available-datasets.cfm. After removing missing cases, 26,145 infants were included in this study based on the infant mortality data that were gathered from reproductive mothers. Infant mortality in binary indicator (yes, no) was considered this study's outcome variable of interest. Based on the findings of previous studies on child mortality, maternal socio-economic, demographic and environmental factors: mother's age at first marriage, mother's body mass index (BMI), administrative division, place of residence, religion, mother's empowerment, mother's occupation, parents education, Mother's media-exposure, mother's age at first birth, birth interval, antenatal care visits, tetanus toxoid (TT) injection, total children ever born, gender of child, birth order, toilet facility, drinking water and type of cooking fuel were considered as infant mortality risk factors.

Statistical methods

Statistical techniques were used in this exploratory study to create an Interpretable SVM model that would extract insightful information regarding infant mortality, based on the workflow shown in Fig. 1. Feature engineering includes fearture transformation, extraction and selection based on the characteristics of the raw data. For feature selection, an SVM model with a linear kernel, where the important features can be determined by comparing the size of the classifier coefficients using the.coef_ argument value in the SVC function of the scikit-learn module in Python 3.7.3 [31], and the conventional chi-square (χ^2) test were employed. In this study, hyperparameter tuning based on Grid search was used to optimize the SVM and LR model parameters (Fig. 1). Using the best parameters, we estimated the SVM and LR models for the entire dataset. Then, we calculated the Akaike Information Criterion (AIC) and Bayesian information criterion (BIC), mean squared error (MSE), and root mean squared error (RMSE) based on the prediction errors. Considering 70% of observations as training data and 30% of observations as test data with different random seed to evaluate ML models' performance using the area under the receiver operating characteristics (ROC) curve (AUC), run-time, and confusion matrix parameters with 100 permutations. In each run, we trained the SVM and LR models with the hyperparameter tuning parameters.

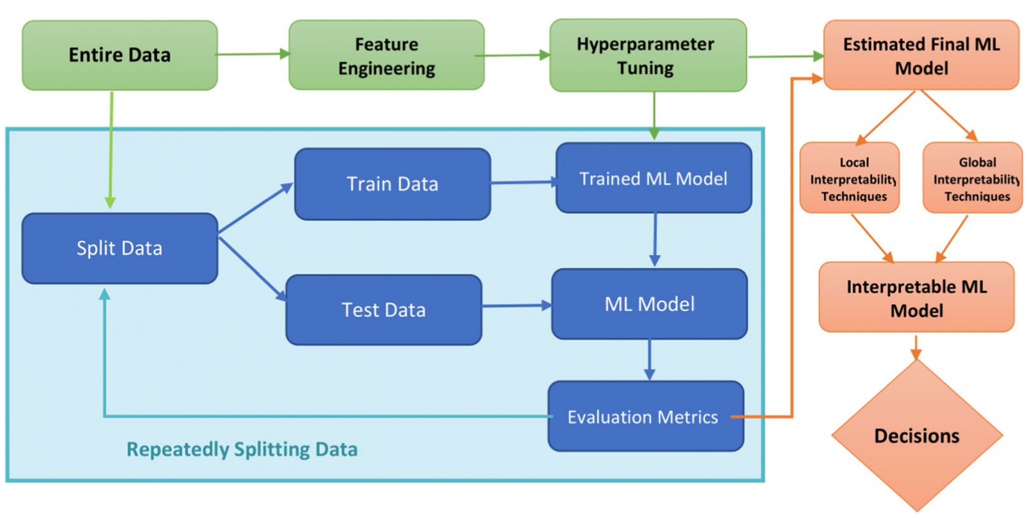

Fig. 1 Work-flow for developing interpretable ML models

From the repeatedly observed performance metrics's distribution, we need to find the best ML model for our study. Subsequently, we estimated that best performed model and employed both local and global interpretability techniques. An interpretable ML model, which can aid in narrowing the performance-interpretability gap and provide more insightful data, was produced by integrating information from both local and global interpretability techniques (Fig. 1). All the analyses were performed using Python 3.7.3, and SPSS version 28.

Logistic regression (LR) model

Let D_i denote the binary dependent variable for the i^{th} observation, and $E_{i1}, \ldots, E_{ip}$ be a set of explanatory variables which can be quantitative or indicator variables referring to the level of categorical variables. Since D_i is a binary variable, it has a Bernoulli distribution with parameter π_i [32]. The dependent of the probability of success on independent variables is assumed to be respectively as,

$$P(D = 1) = \pi_i = \frac{\exp(\beta_0 + \beta_1 E_{i1} + \cdots + \beta_p E_{ip})}{1 + \exp(\beta_0 + \beta_1 E_{i1} + \cdots + \beta_p E_{ip})}. \tag{1}$$

The above relation also can be expressed as,

$$\text{logit}(\pi_i) = \log \frac{\pi_i}{1 - \pi_i} = \beta_0 + \beta_1 E_{i1} + \cdots + \beta_p E_{ip}. \tag{2}$$

The odds ratio with a 95% confidence interval was usually used to explain predictor variables impact.

Support vector machine (SVM)

The SVM is a supervised machine learning algorithm primarily used for classification and regression tasks [33], but here we will focus on its classification application. It aims to find the optimal hyperplane that maximizes the margin between two classes in the input feature space. In more advanced uses, SVM can employ a kernel trick, mapping their inputs into high-dimensional feature spaces to make it possible to perform the linear classification of non-linearly separable data [33, 34]. SVMs use kernel function, which allows intuitively computing the dot products between the converted feature vectors instead of explicitly computing the coordinates of the transformed space and avoids performing costly, pointless calculations for extreme scenarios [35]. The SVM with different kernels,

$$\text{The linear kernel} : k(x, x_i) = x \cdot x_i^T. \tag{3}$$

$$\text{The polynomial kernel with degree } d : \quad k(x, x_i) = \left(1 + x \cdot x_i^T\right)^d. \tag{4}$$

$$\text{The RBF kernel} : k(x, x_i) = e^{-\gamma ||x - x_i||^2}, \text{ where } \gamma > 0. \tag{5}$$

$$\text{The sigmoid kernel} : k(x, x_i) = \tanh\left(\gamma x_i^T x_j + r\right). \tag{6}$$

Model selection criteria

The Akaike Information Criterion (AIC) is a measure of goodness of fit of a statistical model. A lower AIC value indicates a better model. The AIC is defined as

$$\text{AIC} = -2\ln(L) + 2k, \tag{7}$$

where L is the likelihood function of the model parameter given the data and k is the number of parameters in the model. Bayesian Information Criterion (BIC) is another model selection criteria defined as

$$\text{BIC} = -2\ln(L) + k\ln(n), \tag{8}$$

where L is the likelihood function of the model parameter given the data, k is the number of parameters in the model and n is the number of data points. Root Mean Square Error (RMSE) measures the difference between predicted values and the actual observed values, which is defined as

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(y_i - \widehat{y}_i\right)^2} \tag{9}$$

where, n is the number of observations, y_i is the observed value and $\widehat{y}_i$ is the predicted value.

Confusion matrix performance parameters

A confusion matrix is a table that is frequently used to assess the performance of a classification model. It thoroughly explains the model's true and erroneous classifications, comparing the model's predictions against the actual ground truth [32]. By comparing predicted and actual classifications in the form of true positive (TP), false positive (FP), true negative (TN), and false negative (FN), the confusion matrix is used to visually represent the performance of the classification algorithm. Hence, different confusion matrix performance parameters are,

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{10}$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{11}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{12}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{13}$$

$$\text{F1} - \text{Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}. \tag{14}$$

Receiver operating characteristic (ROC) curve

A visual illustration is the ROC curve used to evaluate the diagnostic ability of binary classification systems. The curve compares the true positive rate (TPR) and false positive rate (FPR) for different threshold values [36].

Interpretibility techniques

The local individual conditional expectation (ICE) is a local interpretability technique that plots the individual influences on the average probability. In ICE, each case in $\left\{x_S^{(i)}, x_C^{(i)}\right\}_{i=1}^{N}$ the curve $\widehat{f}_S^{(i)}$ is plotted against $x_S^{(i)}$, while $x_C^{(i)}$ remain fixed [37]. For centered ICE plot, the new plot is defined as,

$$\widehat{f}_{cent}^{(i)} = \widehat{f}^{(i)} - 1\widehat{f}\left(x^a, x_C^{(i)}\right). \tag{15}$$

The global surrogate model is a global interpretability technique that focuses on approximating the predictions of the ML model as accurately as possible and explaining the predictions simultaneously. We aim to closely approximate the black box prediction function f with the interpretable surrogate model prediction function g that is,

$$g(x) = \sum_{m=1}^{M} c_m I\{x \in R_m\}. \tag{16}$$

Results and analysis

Feature selection

Table 1 displays the prevalence of infant mortality as well as the frequency and percentage distributions of exposure variables based on data from 26,145 children from the most recent BDHS 2017–18. The study reveals that infant mortality in Bangladesh was found to be significantly associated with the following factors: the mothers' age at first marriage (p-value = 0.016 < 0.05), their succeeding birth interval (p-value < 0.0001), their BMI (p-value < 0.0001), their level of education (p-value < 0.0001), their occupation (p-value < 0.0001), their mass-media exposure (p-value = 0.007 < 0.05), the total number of births they had (p-value < 0.0001), their family wealth index (p-value < 0.0001), their division of residence (p-value < 0.0001), their religion, the type of cooking fuel (p-value < 0.0001) and toilet (p-value < 0.0001) they used, the gender (p-value < 0.0001), and birth order of their children (p-value < 0.0001), and the father's educational background (p-value < 0.0001). Similar conclusions about important factors influencing infant mortality for BDHS 2017–18 data were reported by [15].

The important factors of infant mortality were examined using SVM with a linear kernel. Using the.coef_ argument value in the SVC function of the scikit-learn module in Python, one can compare the sizes of the classifier coefficients to identify the significant features after SVM was fitted for the complete dataset. The chosen predictors were shown with aqua bars in Fig. 2, while the less significant (i.e., less variance holding) predictors were shown with red bars. The Type of cooking fuel, Successive birth interval, Mother's occupation, Place of residence, Religion, Toilet facility, Birth order number, TT vaccine, Mother's education, Child gender and BMI were the primary features that were selected for this approach.

Fitted SVM and LR models for predicting infant mortality

According to the BDHS, 2017–2018, the prevalence of infant mortality in Bangladesh was 8.94%. As a result, this study presents an imbalanced binary classification problem, meaning there is an unequal distribution between the frequency of outcome events (8.94%) and nonevents (91.06%) in Fig. 3. We avoid using any imbalance correction strategies for this investigation because balancing does not increase prediction performance for powerful classifiers [38] and imbalance correction may significantly decrease model performance [39]. This study optimized the LR and SVM models to predict IM in Bangladesh using hyperparameter tweaking based on the Grid search method. For the LR and SVM models, we had established a variety of search spaces for each parameter. Table 2 shows the search range and determined optimal values for each parameter of the LR and SVM models.

We estimated the LR model with the hyperparameter tuning parameters (tol = 0.001, max_iter = 50, C = 0.1, penalty = l2, solver = saga) and the SVM model with the hyperparameter tuning parameters (tol = 0.001, max_iter = 50, C = 0.01, gamma = scale, kernel = sigmoid) for the entire dataset to predict infant mortality in Bangladesh using the selected predictors in Fig. 2. The prediction errors were estimated from these fitted models. We therefore computed the mean squared error (MSE), root mean squared error (RMSE), Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC), and the outcomes are shown in Table 3. Table 3 reveals that the LR model has an AIC value of -65,110.68 and the SVM model with sigmoid kernel has an AIC value of -50,559.46, therefore, the LR model offered a better fit.

Table 1 Association between socio-demographic characteristics and infant mortality

Characteristics	Infant mortality		χ^2	*p*-value
	Yes (8.93%) *n*(%)	**No (91.06%) *n*(%)**		
Age at first marriage				
< 18 years	1972 (9.1%)	19,614 (90.9%)	5.899	.016*
≥ 18 years	365 (8.0%)	4194 (92.0%)		
Age at first birth				
≤ 20 years	2074 (9.0%)	20,924 (91.0%)	1.486	.231
> 20 years	263 (8.4%)	2884 (91.6%)		
Succeeding birth interval				
≤ 2 years	1161 (18.6%)	5095 (81.4%)	934.931	< .0001**
> 2 years	1176 (5.9%)	18,713 (94.1%)		
TT Injection				
No	2328 (8.9%)	23,748 (91.1%)	1.432	.208
Yes	9 (13.0%)	60 (87.0%)		
Division of residence				
Dhaka	300 (9.2%)	2976 (90.8%)	35.418	< .0001**
Barisal	234 (8.0%)	2702 (92.0%)		
Chittagong	305 (7.2%)	3939 (92.8%)		
Khulna	244 (8.6%)	2582 (91.4%)		
Mymensingh	318 (10.2%)	2804 (89.8%)		
Rajshahi	299 (10.5%)	2560 (89.5%)		
Rangpur	312 (9.5%)	2961 (90.5%)		
Sylhet	325 (9.0%)	3284 (91.0%)		
Place of residence				
Urban	671 (8.5%)	7184 (91.5%)	2.166	.143
Rural	1666 (9.1%)	16,624 (90.9%)		
Mother's educational level				
No education	762 (10.8%)	6293 (89.2%)	65.778	< .0001**
Primary	949 (9.0%)	9585 (91.0%)		
Secondary	560 (7.7%)	6732 (92.3%)		
Higher	66 (5.2%)	1198 (94.8%)		
Father's educational level				
No education	857 (10.1%)	7639 (89.9%)	54.568	< .0001**
Primary	870 (9.5%)	8292 (90.5%)		
Secondary	461 (7.6%)	5570 (92.4%)		
Higher	149 (6.1%)	2307 (93.9%)		
Wealth index				
Poor	1166 (9.7%)	10,828 (90.3%)	20.636	< .0001**
Middle	465 (8.9%)	4761 (91.1%)		
Rich	706 (7.9%)	8219 (92.1%)		
Body mass index				
Underweight	1347 (9.3%)	13,124 (90.7%)	46.296	< .0001**
Normal	350 (11.3%)	2751 (88.7%)		
Overweight & Obesity	640 (7.5%)	7933 (92.5%)		
Religion				
Non-Muslim	223 (10.8%)	1851 (89.2%)	9.103	.003**
Muslim	2114 (8.8%)	21,957 (91.2%)		
Respondent occupation				
Not working	900 (8.2%)	10,061 (91.8%)	12.278	< .0001**
Working	1437 (9.5%)	13,747 (90.5%)		

Table 1 (continued)

Characteristics	Infant mortality		χ^2	*p*-value
	Yes (8.93%) *n*(%)	No (91.06%) *n*(%)		
Women empowerment				
No	1941 (9.0%)	19,592 (91.0%)	.854	.363
Yes	396 (8.6%)	4216 (91.4%)		
Exposure to mass media				
No	1350 (9.4%)	13,056 (90.6%)	7.373	.007**
Yes	987 (8.4%)	10,752 (91.6%)		
Gender of child				
Female	1006 (7.7%)	12,077 (92.3%)	50.208	<.0001**
Male	1331 (10.2%)	11,731 (89.8%)		
Birth order number				
One	1188 (9.7%)	11,027 (90.3%)	17.451	<.0001**
Two and more	1149 (8.2%)	12,781 (91.8%)		
Drinking water quality				
Safe water	2181 (9.0%)	22,113 (91.0%)	.638	.446
Unsafe water	156 (8.4%)	1695 (91.6%)		
Toilet facility				
Hygienic	1271 (8.4%)	13,794 (91.6%)	10.999	<.0001**
Unhygienic	1066 (9.6%)	10,014 (90.4%)		
Cooking fuel				
Less polluted	267 (7.6%)	3259 (92.4%)	9.347	<.0001**
Polluted	2070 (9.2%)	20,549 (90.8%)		
Antenatal care				
No	2327 (8.9%)	23,724 (91.1%)	.335	.584
Yes	10 (10.6%)	84 (89.4%)		
Total children ever born				
1 or 2	179 (3.5%)	4892 (96.5%)	226.111	<.0001**
3 and more	2158 (10.2%)	18,916 (89.8%)		

*Significant at 5% Level of Significance, ** Significant at 1% Level of Significance

Additionally, the LR model provided a superior fit based on the RMSE and BIC values.

To examine the effectiveness of ML classifiers in greater detail, we split the entire dataset into 70% observations as training data and 30% as test data. We conducted 100 permutations to fully comprehend the performance evaluation of the LR and SVM models. In each run, the dataset was divided into 70% of observations for training and 30% of observations for testing, using a predetermined random seed. The results of this analysis were achieved using the scikit-learn module in Python 3.7.3, with random seeds 1980 to 2079 based on 100 permutations for predicting infant mortality in Bangladesh. Table 4 shows infant mortality's predictive performances for the LR model and SVM model with the sigmoid kernel based on 100 permutations, including the run time, area under the curve (AUC), and confusion matrix. The ROC curve (AUC) for the LR model was better than that of the SVM model, but the run-time was slower for the LR model than that of the SVM model. Figure 4 shows the predictive AUC for the LR model and the SVM model with sigmoid kernel using random seeds 1980 and 2079—the initial and final results from the permutation studies. The LR model offers a larger AUC, which outperforms the SVM model in predicting infant mortality. We observed that the test data set contained 7173 negative cases and 671 positive cases using random seed 1980. Nevertheless, the LR model was unable to predict any positive cases, meaning that the true negatives (TN) were 7173, the false negatives (FN) were 671, the false positives (FP) were 0, and the true positives (TP) were 0. However, the SVM model with the sigmoid kernel was able to identify some positive cases, these include TN (6630), FN (611), FP (543), and TP (60) in Table 4.

Table 5 exhibits the summary measures of different performance metrics for the LR and SVM models with random seeds 1980 to 2079 based on 100 permutations. Additionally, Fig. 5 displays the performance metrics'

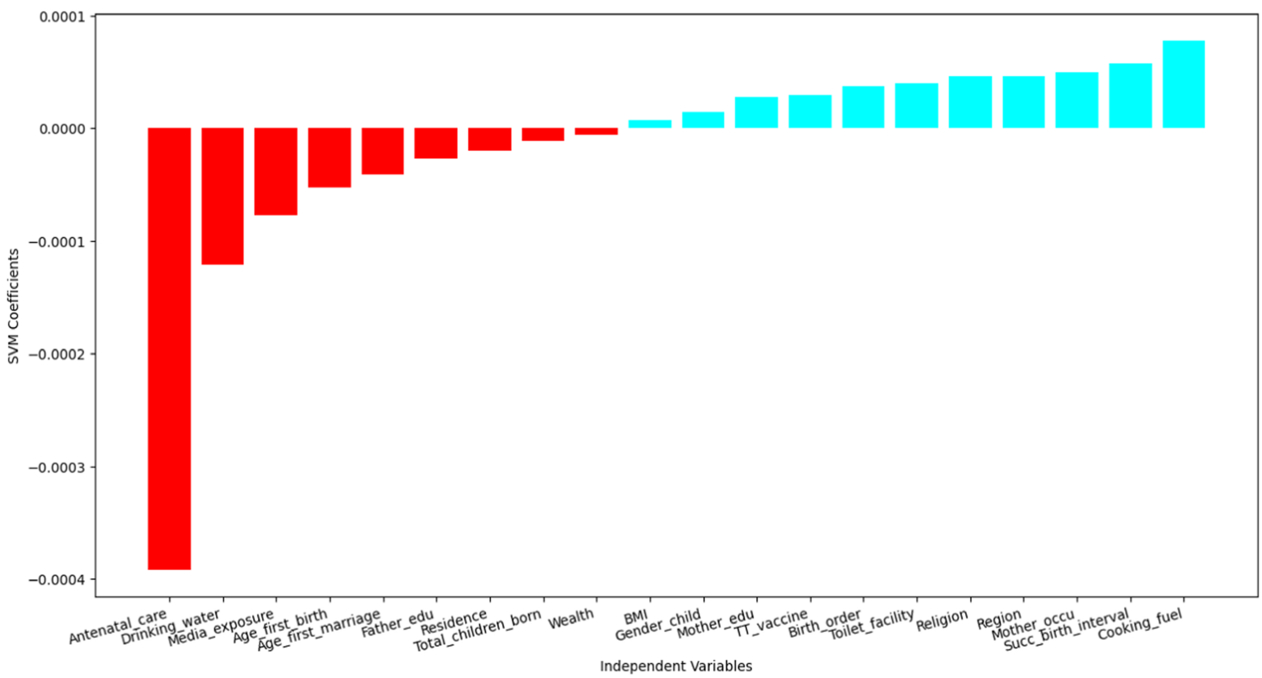

Fig. 2 Important features for predicting infant mortality using the SVM algorithm with linear kernel

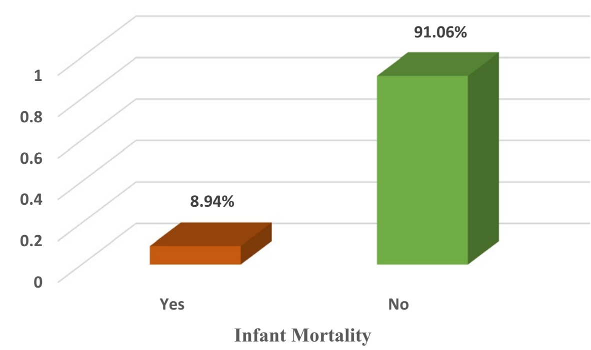

Fig. 3 Prevalence of infant mortality in Bangladesh based on BDHS, 2017–2018

distribution. To compare the performances of the LR and SVM models based on AUC scores, we used the Wilcoxon signed-rank test, in which the null hypothesis (H0) states that the performances of the classifiers are equivalent [40]. Table 5 reveals that the LR and SVM models' performances were not equal according to the Wilcoxon signed-rank test (p-value = 3.89e-18 < 0.05). The LR model showed better accuracy, specificity, and AUC but failed to detect positive instances, resulting in poor performance metrics like sensitivity, precision, and F1-score. Sensitivity measures a machine learning model's ability to detect positive instances, preventing infections by reducing false negatives, and resulting in a higher true positive

Table 2 Hyperparameter tuning using the Gridsearch for the LR and SVM models to predict infant mortality in Bangladesh

Logistic regression	SVM				
Parameters	**Search space**	**Tuned value**	**Parameters**	**Search space**	**Tuned value**
Tol	0.001, 0.0001, 0.0002	0.001	Tol	0.001, 0.0001, 0.0002	0.001
max_iter	10, 50	50	max_iter	10, 50	50
C	10, 1.0, 0.1, 0.01	0.1	C	10, 1.0, 0.1, 0.01	0.01
Penalty	'none', 'l1', 'l2', 'elasticnet'	'l2'	Gamma	'scale', 'auto', 2.1, 1.3	'Scale'
Solver	'newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga'	'saga'	Kernel	'linear', 'poly', 'rbf', 'sigmoid'	'Sigmoid'

Table 3 Model selection criteria and the measures of prediction errors of the LR and SVM model with Sigmoid kernel to predict infant mortality

Model	MSE	RMSE	AIC	BIC
LR	0.0894	0.2989	−63110.68	−63012.62
SVM	0.1445	0.3801	−50559.46	−50461.40

rate. Sensitivity is therefore a crucial performance metric. The SVM model showed improvements in sensitivity, precision, and F1-score in comparison to the LR model. There was also a faster run time for the SVM model.

Interpretation of the outcomes

The LR analysis also showed that newborns were less likely to die (OR = 0.249, 95% CI 0.229 – 0.271, $p < 0.05$) when mothers chose to give birth after a gap of more than two years in Table 6. Mothers with greater educational attainment were shown to have lower infant death rates. Compared to mothers whose BMI was underweight, mothers whose BMI was normal had a higher risk of infant death. Mothers who were overweight or obese had a lower risk of their infants dying than mothers whose BMI was underweight. The infant mortality rate was lower for working mothers than for non-working mothers. The death rate for male infants was higher than that of female infants. Compared to cases of first birth order, infants in positions two or higher had a lower mortality rate. Compared to families with hygienic toilets, those with unhygienic toilets had a lower infant mortality rate. Infant mortality was less common in families that

Table 4 Confusion matrix of Logistic Regression and SVM model with Sigmoid kernel to predict infant mortality for different random seeds based on 100 permutation

Random seed	Logistic regression			SVM with sigmoid kernel		
	Run time	AUC	Confusion matrix	Run time	AUC	Confusion matrix
1980	0.0679	0.6735	[[7173 0] [671 0]]	0.0099	0.5579	[[6630 543] [611 60]]
1981	0.0430	0.6653	[[7143 0] [701 0]]	0.0001	0.5623	[[6544 599] [639 62]]
…	…	…	…	…	…	…
2078	0.0669	0.6624	[[7141 0] [703 0]]	0.0228	0.5713	[[6559 582] [640 63]]
2079	0.0691	0.6900	[[7157 0] [687 0]]	0.0207	0.5742	[[6658 499] [631 56]]

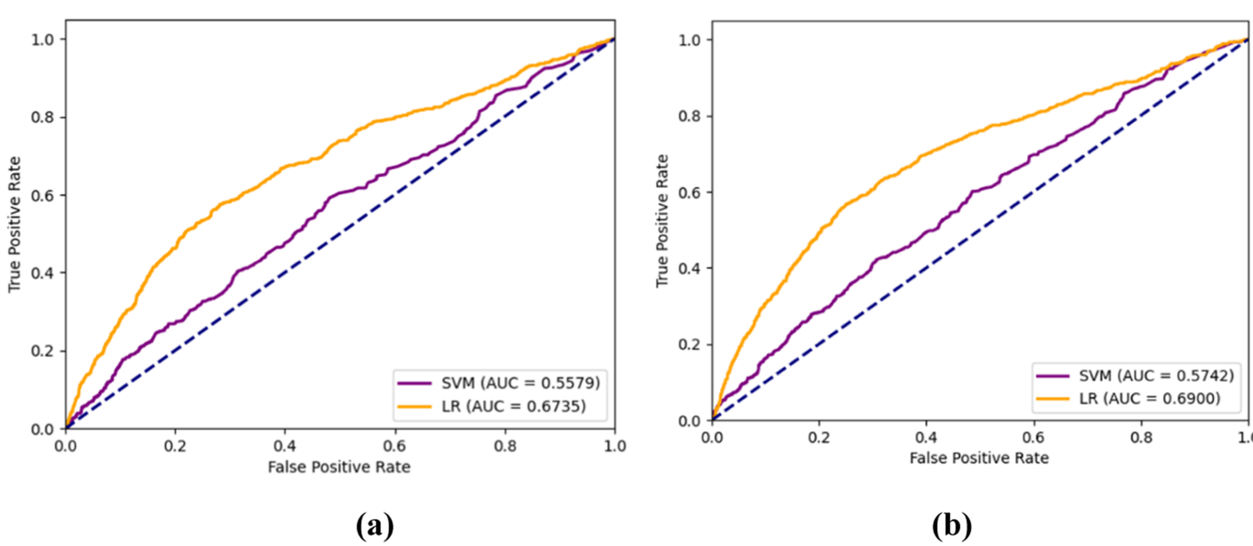

Fig. 4 ROC curves for the LR and SVM models to predict infant mortality in Bangladesh, with random seeds 1980 in (**a**) and 2079 in (**b**)

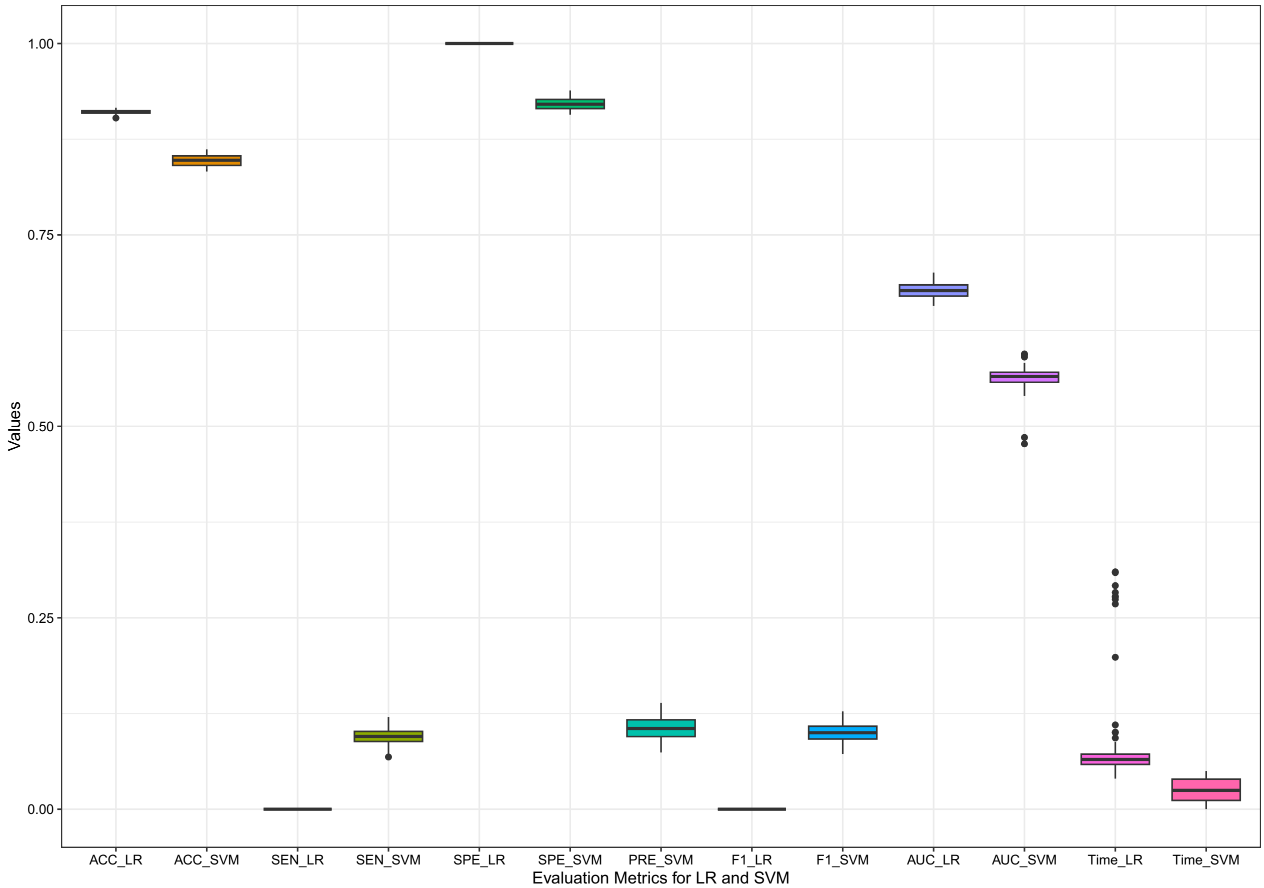

Fig. 5 Box plots of the distribution of performance metrics for the LR and SVM models

Table 5 Accuracy, sensitivity, specificity, precision, F1-score, AUC, and run-time of the LR and SVM models to predict infant mortality based on 100 permutations

Performance metrics		LR	SVM
Accuracy	Mean	0.9105	0.8470
	Standard deviation	0.0025	0.0075
Sensitivity	Mean	0	0.0949
	Standard deviation	0	0.0107
Specificity	Mean	1	0.9209
	Standard deviation	0	0.0077
Precision	Mean	NaN	0.1062
	Standard deviation	NaN	0.0148
F1-score	Mean	0	0.1000
	Standard deviation	0	0.0117
AUC	Mean	0.6780	0.5632
	Standard deviation	0.0095	0.0157
Run-time	Mean	0.0832	0.0254
	Standard deviation	0.0629	0.0154
Wilcoxon signed-rank test		Statistic = 1e-21	*p*-value = 3.89e-18

used polluted cooking fuel than in families that used less polluted fuel.

We analyze the results for predicting infant mortality in Bangladesh from the SVM model using the local individual conditional expectation (ICE) and global surrogate models [37]. The results of the local ICE technique are shown in Fig. 6, where the SVM model with a sigmoid kernel is used to depict individual influences on the average likelihood of dying within the first birthday. Figure 7 shows, with the remaining predictors left unchanged, the correlation between a particular predictor and the likelihood of seeing an infant's death using the global surrogate model.

In Fig. 6, the horizontal lines denote the probability of the "average" newborn babies dying within the first year of birth. The findings show that mothers who gave birth to their first child had a lower risk of infant death than mothers who gave birth to two or more children. Infant deaths were more common in mothers with normal BMIs than in underweight or obese mothers. Mothers who used less polluted cooking fuel were less likely to experience infant deaths for their babies than those who used

Table 6 Odds ratios (OR) with 95% confidence intervals (CIs), and *p*-values obtained from the LR model to predict infant mortality in Bangladesh

Variables	OR	(95% CI)	*p*–value
Succeeding birth interval			
≤ 2 years (ref.)	1.000	–	–
> 2 years	0.249	(0.229–0.271)	< .0001*
TT Injection			
No (ref.)	1.000	–	–
Yes	1.914	(0.926–3.955)	.079
Division of residence			
Dhaka (ref.)	1.000	–	< .0001*
Barisal	0.763	(0.635–0.916)	.004*
Chittagong	0.606	(0.517–0.711)	< .0001*
Khulna	0.777	(.737–1.023)	.006*
Mymensingh	0.902	(0.649–0.930)	.233
Rajshahi	0.989	(0.761–1.069)	.897
Rangpur	0.760	(0.641–0.900)	.002*
Sylhet	0.607	(0.517–0.712)	< .0001*
Mother's educational level			
No education (ref.)	1.000	–	< .0001*
Primary	0.789	(.714– 0.872)	< .0001*
Secondary	0.686	(.610– 0.770)	< .0001*
Higher	0.456	(.350–0.595)	< .0001*
Body mass index			
Underweight (ref.)	1.000	–	< .0001*
Normal	1.135	(0.997–1.291)	.056
Overweight & Obesity	0.770	(0.696–0.851)	< .0001*
Religion			
Non–Muslim (ref.)	1.000	–	–
Muslim	0.512	(0.457– 0.573)	< .0001*
Mother's occupation			
Not working (ref.)	1.000	–	–
Working	0.998	(.910–1.094)	.967
Gender of child			
Female (ref.)	1.000	–	–
Male	1.287	(1.181–1.401)	< .0001*
Birth order number			
One (ref.)	1.000	–	–
Two and more	0.716	(0.656–0.782)	< .0001*
Toilet facility			
Hygienic (ref.)	1.000	–	–
Unhygienic	.977	(.895–1.066)	.599
Cooking fuel			
Less polluted (ref.)	1.000	–	–
Polluted	0.788	(0.693–0.896)	< .0001*

OR = 1 for reference category, *Significant at 1% Level of Significance

polluted cooking fuel. The findings indicate that compared to their female counterparts, male newborns were more likely to die before turning one year old. Higher or secondary-educated mothers were more likely to experience infant deaths than primary-educated and non-educated mothers. Results reveal that working mothers were more likely to have a higher probability of seeing infant deaths of their babies than not-working mothers. Figure 6 also reveals that the northern administrative divisions of Bangladesh have a higher chance of experiencing infant death. The probability of infant deaths was higher in non-Muslim families than in Muslim families. The mothers who gave new birth within two years of the previous birth have a higher chance of experiencing infant mortality than those whose successive birth interval is more than two years. Mothers who used hygienic toilets and were vaccinated were less likely to experience infant deaths of their babies.

Figure 7 explores the outcomes of the global surrogate model by counting the predictions of the SVM model in any given conditions. Our fitted SVM model with the sigmoid kernel reveals that 2296 infant deaths and 23,849 alive were predicted (on average). Our SVM model predicts a higher number of infant deaths when polluted cooking fuel is used in households. Results explore that the fitted SVM counted more infant deaths when households used polluted cooking fuel and successive birth intervals were less than two years. The fitted model predicts more infant deaths for working mothers who also use polluted cooking oil in their households. SVM predicts more infant deaths for working mothers, given that they used less polluted cooking fuel and the birth interval was more than two years. For the mothers who were homemakers and gave birth within two years of the previous one, fitted SVM predicts more infant deaths when they use polluted cooking fuel in their households.

Discussion

Artificial intelligence (AI) is popular for complex decision-making analysis, but interpretation is challenging. Interpretable AI is a flourishing research field that builds ML complete solutions by bridging the gap between performance and interpretability [24, 41]. SVM is a popular ML model known for producing accurate predictions in classification problems [42]. It generates a multidimensional hyperplane that distinguishes classes [33], maximizing the margin between observations and minimizing training errors [34]. SVM has high discriminative ability in small sample sizes and large variables [43–45], and good generalization ability, robustness, and avoidance of overfitting [28], but has difficulty in interpreting results [29]. To the best of our knowledge, two studies have been identified as interpretable AI fields based on the SVM model for healthcare research, i.e., [20] used a hybrid approach based on Quadtree decomposition to interpret the results of medical image analysis, and [21] used local

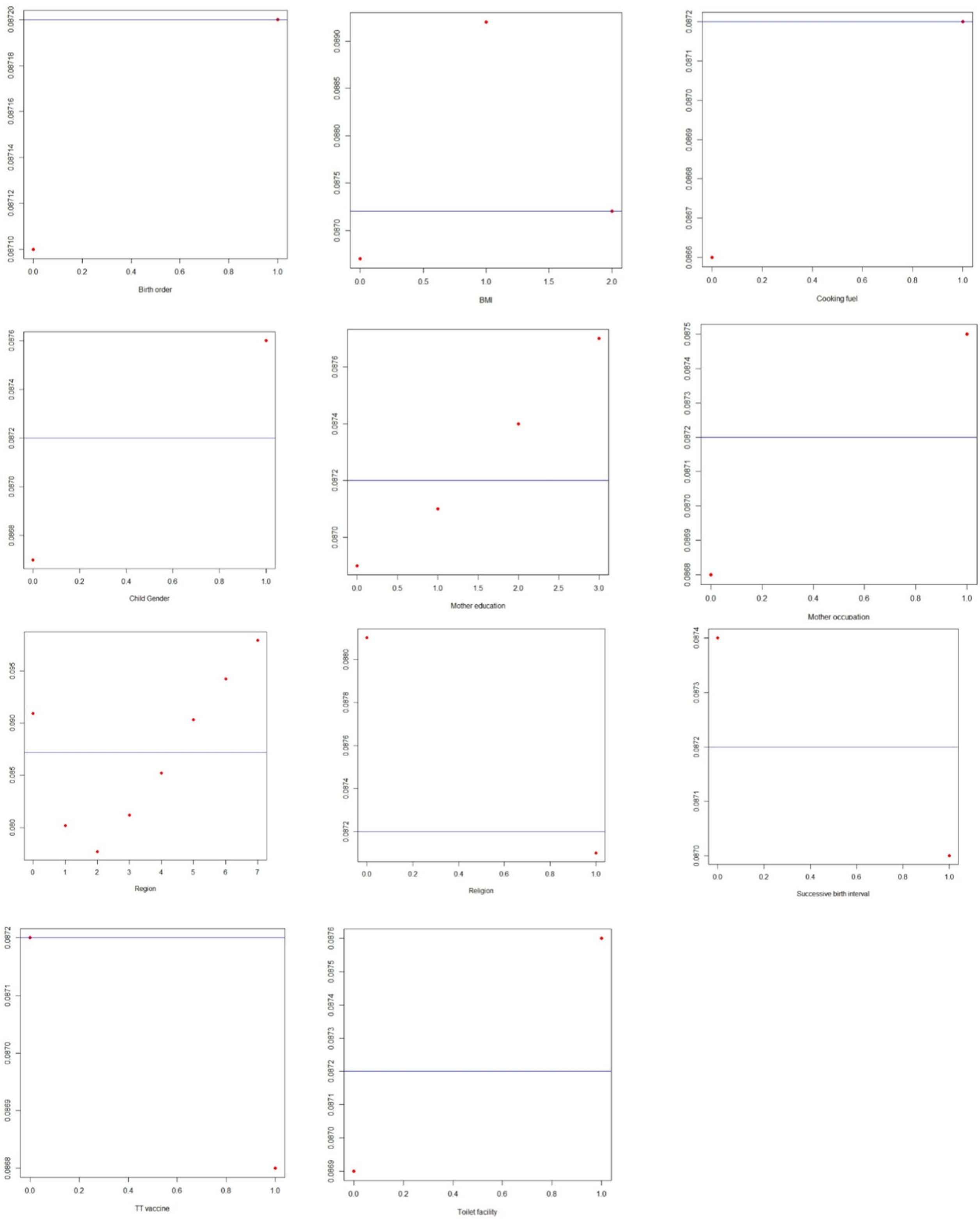

Fig. 6 Impacts of individual predictors on the likelihood of infant mortality for the SVM model using the local ICE technique

Fig. 7 A surrogate tree with terminal nodes of depth equal to 2, 3, and 4 that approximate the predictions made by the SVM trained on the infant mortality BDHS 2017–18 dataset

ICE interpretability techniques to interpret the results of marketing research that classified customer preferences. Moreover, [30] utilized global and local interpretability techniques to interpret hypertension prediction outcomes using the RF model. Global interpretability techniques generalize over the entire population, while local interpretability techniques provide instances-level explanations. Both methods are computationally expensive, but valid depending on application needs, such as healthcare applications [30]. Therefore, this research aimed to predict infant mortality in Bangladesh based on the BDHS 2017/18 data using global surrogate models and local ICE interpretability techniques, enhancing clinicians' understanding and trust in healthcare analytics at local and global levels.

Age at first marriage, Successive Birth interval, Division of residence, Mother's educational level, Father's educational level, Wealth index, Mother's BMI, Religion, Respondent occupation, Exposure to mass media, Gender of child, Birth order number, Toilet facility, Type of cooking fuel, and Total children ever born are the variables that the chi-square test identified as significantly associated with infant mortality in Table 1. In contrast, the most important characteristics to predict infant mortality in Bangladesh are identified by SVM-based feature selection as being the type of cooking fuel, successive birth interval, mother's occupation, place of residence, religion, toilet facility, birth order number, TT vaccination, mother's educational level, child's gender, and mother's BMI. We estimated both the LR model and SVM model with the hyperparameter tuning parameters for the entire dataset to predict infant mortality in Bangladesh using these selected predictors (Fig. 2). Based on the prediction errors, the LR model had an AIC value of −65,110.68, while the SVM model with the sigmoid kernel had an AIC value of −50,559.46 (Table 3). Additionally, the LR model provided a superior fit based on the RMSE and BIC values. The study analyzed the effectiveness of machine learning classifiers in predicting infant mortality in Bangladesh. The dataset was divided into 70% training data and 30% test data, with 100 permutations conducted. The results of the 100 permutations demonstrated that the LR model (Average: accuracy = 0.9105, precision = NaN, sensitivity = 0, specificity = 1, F1-score = 0, area under the ROC curve (AUC) = 0.6780, run-time = 0.0832) outperformed the SVM model (Average: accuracy = 0.8470, precision = 0.1062, sensitivity = 0.0949, specificity = 0.9209, F1-score = 0.1000, AUC = 0.5632, run-time = 0.0254) in predicting infant mortality (Table 5), but the LR model had a slower run-time and it was unable to predict any positive cases. The test data set for random seed 1980 had 671 positive cases and 7173 negative cases, but the LR model was predicted the true negatives (TN) cases were 7173, the false negatives (FN) cases were 671, the false positives (FP) cases were 0, and the true positives (TP) cases were 0 in Table 4. Hence, the LR was unable to predict any positive cases. However, the SVM model with the sigmoid kernel was able to identify some positive cases, these include TN (6630), FN (611), FP (543), and TP (60) in Table 4.

The LR analysis found that infants were less likely to die when mothers gave birth after a gap of over two years (Table 6). Mothers with higher educational attainment had lower infant death rates. Normal BMI mothers had a higher risk of infant death compared to underweight mothers. Overweight or obese mothers had a lower risk. Working mothers had lower infant mortality rates. Male infants had higher death rates than female infants. Infants in positions two or higher had lower mortality rates. Families with polluted cooking fuel had less infant mortality (Table 6).

The study examines Bangladesh's infant mortality prediction based on the SVM model using the local ICE interpretability technique (Fig. 6), which depicts individual influences on the average likelihood of dying within the first birthday. The study results reveal that mothers with normal BMIs, less polluted cooking fuel, and male newborns are more likely to experience infant death. Working mothers are more likely to experience infant deaths than non-working mothers. Infant deaths are more common in non-Muslim families and those who give birth within two years of previous birth. Hygienic toilets and vaccinations are also less likely to cause infant deaths. The northern administrative divisions of Bangladesh have higher infant death rates (Fig. 6). The global surrogate model specifies the correlation between a particular predictor (with the remaining predictors left unchanged) and the likelihood of seeing an infant's death. A fitted SVM model using the global surrogate model predicts 2296 infant deaths and 23,849 alive, with a higher number of infant deaths occurring when households use polluted cooking fuel in Fig. 7. The model also predicts more infant deaths for working mothers who also use polluted cooking fuel in their households, given that they use less polluted fuel and have a birth interval of more than two years. Mothers who give birth within two years of the previous birth also have more infant deaths predicted by the fitted SVM (Fig. 7).

Our findings demonstrate that the type of cooking fuel has a higher significant impact on infant mortality, even when considered alongside other variables such as Successive birth interval and Mother occupation. For instance, mothers who maintained successive birth intervals of less than two years experienced higher child mortality rates when exposed to polluted cooking fuels, which shows that cooking fuel consistently affects them. Evidence from several studies supported our findings that polluted or solid fuels caused more infant deaths [15, 16, 46, 47]. The global surrogate model reveals that mothers who lived in less polluted areas and used clean fuels and hygienic restrooms had lower death rates regardless of other factors. Our study provided strong evidence that a lower birth interval (less than two years) is more responsible for increasing the risk of infant deaths, which is supported by the earlier study [15, 16, 48]. This study also found working mothers, parental poor educational qualifications, reluctance to take the TT vaccine, gender of child and unhygienic toilet facilities have significant impacts on increasing infant deaths. The LR model indicated that working mothers and houses with contaminated cooking fuel had lower infant death rates (Table 6), which fails to reveal the original situation. However, the global surrogate model predicts a higher infant mortality rate among working mothers who use polluted cooking fuel at home (Fig. 7).

Complex ML models, while outperforming simple interpretable models, clinicians struggle to understand and trust these complex ML models due to their lack of intuition and explanation of their predictions. By utilizing the global surrogate model and the local ICE interpretability technique, we were able to predict infant mortality in Bangladesh and interpret the findings of the SVM models based on the BDHS 2017–18 data. This improved clinicians' understanding and trust in healthcare analytics, enabling them to take further initiatives and interventions for stakeholders and policymakers. One of our study's limitations is that we could have improved our results by using the globa surrogate model with terminal nodes of depth equal to 2–8 instead of 2–4 and some more other interpretability techniques. Furthermore, the cross-sectional BDHS data, which is derived from a national survey, might contain some biases. These could be addressed as a study limitation. However, our developed interpretable SVM model reveals global interpretations help clinicians understand the entire conditional distribution, while local interpretations focus on specific instances, providing different insights into model behavior.

Conclusion

Data scientists are increasingly focusing on explaining the predictions of black-box ML models, not just achieving optimal performance, but also explaining at both global and local levels. An interpretable SVM model can help to close the performance-interpretability gap and offer more meaningful analysis for complex and important decision-making processes.

Acknowledgements
The authors would like to acknowledge the Bangladesh Demographic and Health Survey (BDHS) authority for the freely available secondary data.

Author contributions
Md. Abu Sayeed (MAS) contributed to the data preparation, implementation of the study, analysis, interpretation of results, and drafted manuscript. Azizur Rahman (AR) contributed to reviewing literature and theoretical knowledge development, review, and editing. Atikur Rahman (ATR) gave invaluable input in the acquisition and preparation of the data, review, and editing. Rumana Rois (RR) conceptualized the research idea, design and supervised the study. The final version is approved by all authors.

Funding
This research received no specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Data availability statement
We used secondary data came from the Demographic and Health Surveys (DHS) Program. The data are accessible online at https://dhsprogram.com/data/available-datasets.cfm.

Declarations

Ethical approval
This article does not include any human participant data conducted by any authors. ICF Macro Institutional Review Board and the National Research Ethics Committee of the Bangladesh Medical Research Council approved the Bangladesh Demographic and Health Survey (BDHS). Participants in relation to this survey gave written consent before the interview. All identification of the survey participants was de-identified before publishing the data. In this study, we used the secondary data freely available on the DHS website: https://dhsprogram.com/data/available-datasets.cfm.

Consent for publication
Not applicable.

Competing interests
The authors declare that they have no competing interests.

Author details
[1]Department of Statistics and Data Science, Jahangirnagar University, Dhaka, Bangladesh.

Received: 13 July 2024 Accepted: 15 September 2024
Published online: 27 October 2024

References

1. McGuire JW. Basic health care provision and under-5 mortality: a cross-national study of developing countries. World Dev. 2006;34(3):405–25.
2. Razzaque A, Chowdhury R, Mustafa AG, Begum F, Shafique S, Lawton A, Islam MZ. Levels, trends and socio-demographic determinants of infant and under-five mortalities in and around slum areas of Dhaka city. Bangladesh SSM-Population Health. 2022;17:101033.
3. National Institute of Population Research and Training (NIPORT); ICF International. Bangladesh Demographic and Health Survey 2017–18. Dhaka, Bangladesh, Rockville, Maryland, USA NIPORT ICF. 2020;1–511.
4. WHO. Infant mortality rate (between birth and 11 months per 1000 live births). WHO Publ. 2023 , Available from: https://www.who.int/data/gho/indicator-metadata-registry/imr-details/1.
5. ReliefWeb. Levels & Trends in Child Mortality: Report 2022—World | ReliefWeb [Internet]. [cited 2023 Sep 10]. Available from: https://reliefweb.int/report/world/levels-trends-child-mortality-report-2022?gclid=CjwKCAjwr_CnBhA0EiwAci5siu9Qwve-8xS9hYSTsaXfiE2Uqb8kRVvP54A0LNhoGzMttfNh_oMaMhoC7k8QAvD_BwE.
6. Sharrow D, Hug L, Liu Y, Lindt N, You D. Levels and trends in child mortality report 2022. 2023. Available from: https://repository.gheli.harvard.edu/repository/12113/.
7. UNICEF. Levels and trends in child mortality, report December 2021. 2021. Available from: https://repository.gheli.harvard.edu/repository/12113/.
8. Rahman AE, Hossain AT, Siddique AB, Jabeen S, Chisti MJ, Dockrell DH, El Arifeen S. Child mortality in Bangladesh–why, when, where and how? A national survey-based analysis. J Global Health. 2021;11:04052.
9. Chowdhury AMR, Bhuiya A, Chowdhury ME, Rasheed S, Hussain Z, Chen LC. The Bangladesh paradox: exceptional health achievement despite economic poverty. Lancet. 2013;382:1734–45. https://doi.org/10.1016/S0140-6736(13)62148-0.
10. United Nations. The sustainable development goals report. United Nations Publ [Internet]. 2017 [cited 2023 Sep 10];1–56. Available from: https://www.un-ilibrary.org/content/books/9789210582599.
11. DaVanzo J, Hale L, Razzaque A, Rahman M. The effects of pregnancy spacing on infant and child mortality in Matlab, Bangladesh: how they vary by the type of pregnancy outcome that began the interval. Popul Stud. 2008;62(2):131–54.
12. Dancer D, Rammohan A, Smith MD. Infant mortality and child nutrition in Bangladesh. Health Econ. 2008;17(9):1015–35.
13. Baqui AH, Rosen HE, Lee ACC, Applegate JA, El Arifeen S, Rahman SM, Black RE. Preterm birth and neonatal mortality in a rural Bangladeshi cohort: implications for health programs. J Perinatol. 2013;33(12):977–81.
14. Vijay J, Patel KK. Risk factors of infant mortality in Bangladesh. Clin Epidemiol Global Health. 2020;8:211–4.
15. Rahman A, Hossain Z, Kabir E, Rois R. Machine learning algorithm for analysing infant mortality in Bangladesh. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 13079 LNCS*, 2021, 205–219. https://doi.org/10.1007/978-3-030-90885-0_19
16. Rahman A, Hossain Z, Kabir E, Rois R. An assessment of random forest technique using simulation study: illustration with infant mortality in Bangladesh. Health Inf Sci Syst. 2022. https://doi.org/10.1007/s13755-022-00180-0.
17. Rois R, Hasan F, Yasmin MN. Prediction of Infant Mortality in Bangladesh Using SVMs, Journal of Medical and Health Sciences. 2021;10(11).
18. Rice SB, Nenadic G, Stapley BJ. Mining protein function from text using term-based support vector machines. BMC Bioinformatics. 2005;6:1–11.
19. Ng KLS, Mishra SK. De novo SVM classification of precursor microRNAs from genomic pseudo hairpins using global and intrinsic folding measures. Bioinformatics. 2007;23:1321–30.
20. Shukla P, Verma A, Abhishek Verma S, Kumar M. Interpreting SVM for medical images using Quadtree. Multimed Tools Appl. 2020;79:29353–73.
21. Nalbantov, G., Bioch, J. C., & Groenen, P. J. Solving and interpreting binary classification problems in marketing with SVMs. In from data and information analysis to knowledge engineering: Proceedings of the 29th Annual Conference of the Gesellschaft für Klassifikation eV University

of Magdeburg, 2005 (pp. 566–573). Berlin, Heidelberg: Springer Berlin Heidelberg.
22. Yu W, Liu T, Valdez R, Gwinn M, Khoury MJ. Application of support vector machine modeling for prediction of common diseases: the case of diabetes and pre-diabetes. BMC Med Inform Decis Mak. 2010;10:1.
23. Ayatollahi H, Gholamhosseini L, Salehi M. Predicting coronary artery disease: a comparison between two data mining algorithms. BMC Public Health. 2019;19:1–9.
24. Barakat N, Bradley AP, Barakat MNH. Intelligible support vector machines for diagnosis of diabetes mellitus. IEEE Trans Inf Technol Biomed. 2010;14:1114–20.
25. Chan CL, Chen CL, Ting HW. An excellent mortality prediction model based on support vector machine (SVM)–A pilot study. 3CA 2010–2010 International Symposium on Computer, Communication, Control and Automation. 2010;134–7.
26. Dimitrios, Antonia G, Clemens S, Nicholas N, Dolores H, Acevedo-Garcia. Predicting Infant Mortality Risk from Information Available at the Time of Birth [Internet]. Popul. Assoc. Am. Annu. Meet. Austin, Texas, USA. 2019. Available from: https://paa2019.populationassociation.org/uploads/191323
27. Saravanou A, Noelke C, Huntington N, Acevedo-Garcia D, Gunopulos D. Predictive modeling of infant mortality. Data Min Knowl Discov. 2021;35:1785–807. https://doi.org/10.1007/s10618-020-00728-2.
28. Bhavsar H, Ganatra A. A comparative study of training algorithms for supervised machine learning. Int J Soft Comput Eng. 2012;2:74–81.
29. Wanner J, Herm L-V, Heinrich K, Janiesch C. Stop ordering machine learning algorithms by their explainability! an empirical investigation of the tradeoff between performance and explainability BT–responsible AI and analytics for an ethical and inclusive digitized society. In: Griva A, Pouloudi N, Dwivedi YK, Pappas I, Mäntymäki M, editors. Dennehy D. Cham: Springer International Publishing; 2021. p. 245–58.
30. Elshawi R, Al-Mallah MH, Sakr S. On the interpretability of machine learning-based model for predicting hypertension. BMC Med Inform Decis Mak. 2019;19:1–32.
31. Garreta R, Moncecchi G. Learning scikit-learn: machine Learning in Python. Birmingham: Packt Publishing; 2021.
32. Awad M, Khanna R. Efficient learning machines: theories, concepts, and applications for engineers and system designers. New York: Apress Media LLC; 2015. https://doi.org/10.1007/978-1-4302-5990-9.
33. Vapnik VN. The nature of statistical learning theory. Nat Stat Learn Theory. 1995. https://doi.org/10.1007/978-1-4757-3264-1.
34. Burges CJC. A tutorial on support vector machines for pattern recognition. Data Min Knowl Discov. 1998;2:121–67.
35. Patle A, Chouhan DS. SVM kernel functions for classification. In: 2013 International Conference on Advances in Technology and Engineering ICATE 2013 2013. https://doi.org/10.1109/ICAdTE.2013.6524743.
36. Fawcett T. An introduction to ROC analysis. Pattern Recognit Lett. 2006;27:861–74. https://doi.org/10.1016/j.patrec.2005.10.010.
37. Christophm. Interpretable machine learning 2023. https://christophm.github.io/interpretable-ml-book/global.html (Accessed September 17, 2023).
38. Elor Y, Averbuch-Elor H, To SMOTE, or not to SMOTE?. arXiv preprint. 2022. arXiv:2201.08528.
39. van den Goorbergh R, van Smeden M, Timmerman D, Van Calster B. The harm of class imbalance corrections for risk prediction models: illustration and simulation using logistic regression. J Am Med Inform Assoc. 2022;29(9):1525–34.
40. Demšar J. Statistical comparisons of classifiers over multiple data sets. J Mach Learn Res. 2006;7:1–30.
41. Chen S, Gao C, Zhang P. Incorporation of data-mined knowledge into black-box SVM for interpretability. ACM Trans Intell Syst Technol. 2022. https://doi.org/10.1145/3548775.
42. Baboo SS, Sasikala S. Multicategory classification using an extreme learning machine for microarray gene expression cancer diagnosis. 2010 IEEE International Conference on Communication Control and Computing Technologies ICCCCT 2010. 2010;10:748–57.
43. Zhu G, Blumberg DG. Classification using ASTER data and SVM algorithms: The case study of Beer Sheva, Israel. Remote Sens Environ [Internet]. 2002 [cited 2023];80:233–40. Available from: https://consensus.app/details/classification-results-also-show-approach-based-zhu/00f48409062451cfb3aaba37cead3f86/.
44. Lai KX, Phung BT, Blackburn TR. Application of data mining on partial discharge part I: Predictive modelling classification. IEEE Trans Dielectr Electr Insul [Internet]. 2010 [cited 2023];17:846–54. Available from: https://consensus.app/details/results-indicate-method-terms-classification-accuracy-lai/1207d4456d35580d9ddb51335ac414e4/
45. Pal M, Mather PM. Support vector machines for classification in remote sensing. Int J Remote Sens [Internet]. 2005 [cited 2023 Sep 11];26:1007–11. Available from: https://consensus.app/details/results-show-achieves-level-classification-accuracy-pal/fea30594fc115267b0e46a4d689f9113/
46. Akinyemi JO, Adedini SA, Wandera SO, Odimegwu CO. Independent and combined effects of maternal smoking and solid fuel on infant and child mortality in sub-Saharan Africa. Trop Med Int Heal. 2016;21:1572–82.
47. Rinne ST, Rodas EJ, Rinne ML, Simpson JM, Glickman LT. Use of biomass fuel is associated with infant mortality and child health in trend analysis. Am J Trop Med Hyg. 2007;76:585–91.
48. Hobcraft J, McDonald JW, Rustein S. Child-Spacing Effects on Infant and Early Child Mortality Author (s): John Hobcraft , John W. McDonald and Shea Rutstein Published by : Office of Population Research Stable URL : http://www.jstor.org/stable/2737284 JSTOR is a not-for-profit service tha. 2016;49:585–618.

Publisher's Note