

Comparison of performance of different statistical machine learning algorithms to predict Child Survival status in North-Eastern states of India

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ABSTRACT

In today's modern world, reducing child mortality rates are the primary health priority in developing countries like India. Identifying determinant factors of under-five child mortality will support notifying parents, health policymakers, and practitioners to adopt effective and efficient actions to improve child health, altering the children's future. This study aims to develop different predictive models to classify children under five (alive or dead) survival status. A logistic regression algorithm is employed to extricate novel factors associated with child death that can serve as targets for intervention. The four commonly used machine learning algorithms- Logistic Regression (LR), K-Nearest Neighbors (KNN), Naïve Bayes (NB), and Support Vector Machine (SVM) are employed to design a predictive model of child survival status, using National Family Health Survey (NFHS-4) 2014-15 data. This work contributes to exploring the possibilities of using supervised learning algorithms to classify children effectively. The predictive performance measures used for classification are precision, recall, f1-measure, ROC (receiver operating characteristics curve), and AUC (area under ROC curve). Our findings reveal Logistic Regression makes the best classification accuracy.

Keywords: Child mortality, supervised learning, ROC.

Mathematics Subject Classification : 62-08, 62R07

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1. Introduction

Globally a figure of 7.4 million children, adolescents, and youth have lost lives due to treatable and preventable diseases in 2019. The current trend predicts that nearly 48 million children below five years will meet the same fate in this decade, 2020-2030. Although there is a decline in the mortality rate by 60% under-five globally from 93 deaths to 38 deaths per 1000 live births in 1990 and 2019, respectively, around 5.2 million children died in 2019 before attaining five years of age (United Nations, 2020). The United Nations (UN) sustainable development targets all member nations to have a minimal death rate under-five age 25 or below deaths per 1000 live births by 2030. To attain the UN

target, it is important to introduce more child health intervention programs, high quality, affordable care, self-provision of a life-saving method for women, children, and young adults.

(Aheto, 2019) uses multilevel Logistic Regression to build a predictive model of child survival status. Although the child survival revolution made significant progress in reducing child mortality, challenges remain to avert preventable under-5 deaths in the coming years and speed up progress in further improving child survival. Urgent actions are required, particularly in sub-Saharan Africa and South Asia, including India, where under-5 mortality rates are high.

(Tesfaye et al., 2017) compares three different machine learning models to find the high predictable model and identify the determinants for child mortality. (Kalyani et al., 2010) proposes SVM in the classification phase of the pattern recognition approach and shows SVM gives a fairly high classification accuracy than other classifiers. (Azar, D. et al., 2018) presents a comparative study of nine machine learning techniques for disease classification. (Hamdi et al., 2009) presents a work of classification method KNN, which was used to classify regions as malignant or benign microcalcifications.

Classification breaks data samples into different classes. The classification technique predicts the class label for each data point. For example, using the classification technique, each child can be classified as "Alive" or "Dead." It is a supervised machine learning technique having a known class label. Classification has two methods binary and multilevel. Only two possible classes may be considered in binary types, such as whether a child is alive or not.

In comparison, the multiclass method has more than two target classes; for example, child death may be classified as "infant death," "post-neonatal death," and "neonatal death." Data is divided into two subsets: training and test datasets. Using train data, we trained the classification technique or classifier. The predictive performance of the classifier could be tested using a test dataset. Nowadays, Healthcare organizations widely use the Classification technique. The study was conducted to predict the accurate and efficient under-5 deaths by using multivariate techniques: Logistic Regression, Naïve Bayes Classifier, Support Vector Machine, and k Nearest Neighbors and identify the best method for prediction of under-5 deaths.

2. Materials and Methods

2.1 Data

For this study, we used data extracted from the 4th round of the National Family Health Survey (NFHS-4), a nationally representative Indian household survey. The survey was conducted by the International Institute of Population Science as a nodal agency and interviewed women aged 15-49 years and men aged 15-54. It is a large-scale sample survey covering all states of India, which collects information on household socioeconomic characteristics, water, and sanitation, health insurance, the number of deaths in the family in the three years preceding the survey, etc. Information on the woman's characteristics, marriage, fertility, children's immunizations and childcare, nutrition, contraception, reproductive health, sexual behavior, HIV/AIDS, domestic violence, etc. According to (Bora & Saikia, 2018), NFHS-4 piled up information from 601,509 households, 699,686 women, and 112,122 men.

And the extracted North-East data consist of 37167 samples. The sample size for this study is 36582 women, of which 1363 under-five children are reported dead, and a total of 35214 under-five children are remained alive. This data was downloaded from www.dhsprogram.com.

2.2 Methods

Our variable of interest in this study is child survival status classified as being alive (coded as 1) or dead (coded as 0). The variables that were supposed to be not meant for the study, such as case id, interview date, household number, etc., were terminated from the analysis. First, we targeted finding a subset of variables that might be considered determinants of child mortality. Out of the 1341 variables of the NFHS-4 survey, 28 variables are taken, assuming they are most relevant to the outcome variable and included in our statistical model. We used stepwise logistic Regression in SPSS to examine the statistically significant variables. Table 1 shows the set of variables used further for classification. Unlike traditional Regression, in which the effects of all selected variables are accounted for without considering their contribution during the specific study, stepwise logistic Regression evaluated and yielded a useful set of variables and checked the importance of variables. It enables us to screen out many unutilized variables during the study.

This study operates supervised machine learning models, i.e., the classification that involves predicting a class label. Supervised learning is essentially a task of learning from data which means it acquires skill or knowledge from experience. It consists of working on a model to know the relationship between explanatory and the outcome variables. They learn from the data and identify patterns, and then models fit based on the given training data labeled the outcomes. The specified best-fit model is then used to predict the outcomes of the test dataset. To predict the test dataset, we provide only the explanatory variables, and then the outputs given by the model are compared to the withheld target variables. And thus, we estimate the skill of the model.

The data set is split into two subsets for any machine learning task: training and test datasets. The training data is used to build our model. In contrast, the test dataset checks whether predicted outcomes are similar to the actual results. We randomly assigned 10%(3647), 15%(5502), 20%(7379), 25%(8937), and 30%(10847) of the sample as our test dataset and the remaining 90%(32935), 85%(31080), 80%(29203), 75%(27645), and 70%(25735), as training data set. All models have been first trained on the training dataset. We estimated the metrics for evaluating the model's accuracy using the test dataset.

We used Logistic Regression to provide greater insight into meaningful variables across approaches and compared four machine learning algorithms K-Nearest Neighbors, Support Vector Machine, Naive Bayes, and Logistic Regression. These models were selected based on their continued popularity among health researchers and practitioners. The public health community incorporates an emerging statistical analytical technique for evaluating big health data (Mooney & Pejaver, 2018). We conducted all analyses using SPSS for stepwise Regression and R for classification to develop the predictive algorithms.

2.2.1 Logistic regression

We first used Stepwise Logistic Regression using SPSS, with child alive as a dependent variable, and all the selected variables as independent variables (predictor variables) and no cross-validation. In a dataset with many predictor variables, there is the possibility of vulnerable to multicollinearity and overfitting (Raj et al., 2020). The stepwise Logistic Regression model allows the removal of redundant variables. Once predictor variables selection was made, we applied the Logistic Regression model for classification in R, where we made the selected variables as input variables.

2.2.2 K-Nearest Neighbors

K-Nearest Neighbors is one of the traditional classification algorithms employed in different classification areas. It is instance-based learning and non-parametric method used for both classification and Regression. It does not assume any functional form of the data (Dey et al., 2016). For any test observation x_i , first, the KNN classifier identifies the nearest K points to x_i from the training data where K is a predefined positive integer. Those selected K points were represented by $\mathcal{N}_0$. Then the conditional probability for class j is estimated as the fraction of points in $\mathcal{N}_0$ whose response values equal j:

$$P(Y = j | X = x_i) = \frac{1}{K} \sum_{j \in \mathcal{N}_0} I(y_i = j).$$

Later, KNN applies the Bayes rule for prediction. The class of test observation (x_i) is assigned as the class with the largest probability (Casella et al., 2006).

2.2.3 Naïve Bayes Classifiers

A probabilistic classifier, Naïve Bayes is a popular supervised Bayesian network classifier. The notion behind the Naïve Bayes algorithm is to find the posterior probability of a data point x_i in a class c_j of the data model. The posterior probability $P(x_i | c_j)$, known as a score of the class, decide the label of x_i . By assuming independence of the features X_k , the posterior probability $P(x_i | c_j)$ can be estimated by multiplying all probabilities of all attributes of the data point in the model:

$$P(x_i | c_j) = \prod_{k=1}^p P(x_{ik} | c_j)$$

Where p is the Number of attributes in each data point or instance.

Equivalently, the Naïve Bayes model assumes the independence of the features X_k for a given class $C=j$:

$$f_j(X) = \prod_{k=1}^p f_{jk}(X_k)$$

The posterior probability for every class is calculated and predicts the instance' level with the highest probability (Karim & Rahman, 2013). Despite these strong assumptions, Naïve Bayes classifiers often perform satisfactorily in many domains (Dey et al., 2016; Hastie, 2009)

2.2.4 Support Vector Machine

The purpose of classification is to identify the survival status of children, whether they are alive or not. Classifiers classify a child as survive or dead by making a classification decision based on the function of features. SVM is a binary classification method used to construct decision boundaries for classification. It is an extension of support vector classifiers that involves enlarging feature space in a specific way (Casella et al., 2006; Hastie, 2009)

We assume that our training data consists of n samples of points $x_i \in \mathbb{R}^p$ with $i=1,2,\dots,n$. Each point x_i belongs to either one of the two classes labeled as $y_i \in \{1, -1\}$. The idea behind SVM is to establish an optimal separating hyperplane that divides the training points into two separated classes so that the margin (M) of separation between two classes is maximum (Hastie, 2009; Lakshmi et al., 2013). The optimal hyperplane must satisfy the following minimization constraint.

$$\begin{aligned} & \min \|\beta\| \\ \text{subject to} \quad & y_i(x_i^T \beta + \beta_o) \geq 1, i=1,2,\dots,n \end{aligned} \quad (1)$$

Suppose that observations in the training data are linearly nonseparable, i.e., classes overlap in feature space. One approach to deal with this situation is to maximize M still and allow some points to be on the wrong side of the margin. Slack variables $\xi = (\xi_1, \xi_2, \dots, \xi_n)$ was introduced and modified the constraints in (Eqn 1) so that the optimization problem becomes

$$\begin{aligned} & \min \|\beta\| \\ \text{subject to} \quad & \begin{cases} y_i(x_i^T \beta + \beta_o) \geq 1 - \xi_i \forall i, \\ \xi_i \geq 0, \sum \xi_i \leq c. \end{cases} \end{aligned} \quad (2)$$

where $M = 1/\|\beta\|$, ξ_i is misclassification error, the constant c is a nonnegative tuning parameter.

Once we solved the equation (Eqn 2), given the solutions $\hat{\beta}_o$ and $\hat{\beta}$, we classify a test observation x based on the sign, and the decision function is

$$\hat{G}(x) = \text{sign}[x^T \hat{\beta} + \hat{\beta}_o].$$

When there is a situation that linear SVM does not perform well, nonlinear SVM is suggested. In that case, we make the procedure more flexible by enlarging features space using polynomials or splines. Generally, linear decision boundaries in the enlarged space achieve better class separation and transform to nonlinear boundaries in the original space (Hastie, 2009).

With nonlinear function, $\hat{f}(x) = \sum_{i=1}^n \hat{\alpha}_i y_i K(x, x_i) + \hat{\beta}_o$,

where $K(x, x_i) = (1 + \langle x, x_i \rangle)^d$

The classifier is $\hat{G}(x) = \text{sign}(\hat{f}(x))$.

This work attempts to analyse the status of child survival and identify children who have high chances of death. Parents or health care professionals, or any concerning people can ensure special attention for them to prevent death. Our interest is both children alive and dead. So, we assessed the evaluation metric of classification, i.e., the Receiver operating characteristic curve (ROC) and area under the

Receiver operating characteristic curve (AUC). The ROC is a plot of two parameters: false-positive rate and true positive rate. The curve plots false-positive rates along the x-axis vs. true positive rates along the y-axis at different classification thresholds (Sanchez et al., 2021). AUC gives the chances that a randomly selected observation (i.e., survey participant) who had a child died (Raj et al., 2020)

3. Results

Our interest is to see how effective the model is based on the metrics and datasets. The different metrics of evaluation of model performance are here to check the efficiency of the algorithm. To calculate the model's performance, we use accuracy, precision, recall, f1-measure, ROC, and AUC to measure the performance of the classification model. The classification accuracy is simply the ratio of the units of correct predictions and a total number of a prediction made by the classifiers. The accuracy of 97% means that in every 100 units, 97 are genuinely classified to their corresponding classes.

Table-1 Variables selection for classification

Name of the variables	S.E.	Wald	P-value	Exp(B)
Source of drinking water	.030	3.501	.061	1.057
Type of toilet facility	.053	8.087	.004	1.163
Main roof material	.091	15.132	.000	1.425
Number of household members (listed)	.020	46.608	.000	.872
Number of children 5 and under in household (de jure)	.080	1083.494	.000	14.136
Type of cooking fuel	.091	17.592	.000	1.468
Total children ever born	.094	2416.224	.000	.010
Number of living children	.069	1435.024	.000	13.892
Birth order number	.079	938.507	.000	11.319
Child is twin	.283	13.271	.000	2.804
Sex of child	.078	16.006	.000	.730
Place of delivery	.084	6.111	.013	1.232

As seen in Table 2, SVM obtained the highest overall classification accuracy with 98%, and the LR got the second-best accuracy with 98% and 97% for different training sizes. As it has been pointed out that the data used in this study is imbalanced, it cannot deduce SVM is a better classifier than others based on the accuracy rate. We demand a supplemental survey of another metric of evaluation. For each model of LR and SVM, both precision and recall for children alive are high, indicating the predictive performance on Response yes, i.e., "Child is Alive" is good. All the precision, recall, and F1 measure for the child alive are 0.99 for the SVM model, and that of the LR model is 0.98(precision), 0.99(recall), and 0.99(F1 measure). In NB and KNN classifiers models, the false-positive rate is also high even if both precision and recall for children alive are high. Hence, both the KNN and NB are not good classifiers for this dataset. Subject to child dead (Response no), when training size is 31080, the

LR model gets the precision value of 0.72 and recall value of 0.62. And when the training size is 32935, SVM models give a precision value of 0.70 and recall 0.72.

The LR method gives an accuracy of classification (98%) and AUC (0.96) while SVM accuracy of classification (98%) and AUC of 0.86. The AUC value of 0.96 describes four out of a hundred children who died due to preventable causes.

Table 2: Performance measures of different classifiers at different training sizes

Size of train data (%)	Alg.	Acc.(%)	Prec. (yes)	Prec. (no)	Rec. (yes)	Rec. (no)	F1 (yes)	F1 (no)
70	LR	98	0.98	0.78	0.99	0.56	0.99	0.65
75	LR	98	0.98	0.71	0.99	0.54	0.99	0.62
80	LR	98	0.98	0.74	0.99	0.53	0.99	0.62
85	LR	98	0.99	0.72	0.99	0.62	0.99	0.67
90	LR	97	0.98	0.70	0.99	0.52	0.99	0.60
70	KNN	97	0.97	1.00	1.00	0.13	0.98	0.23
75	KNN	97	0.97	0.98	1.00	0.15	0.98	0.26
80	KNN	97	0.97	0.94	1.00	0.18	0.98	0.30
85	KNN	97	0.97	1.00	1.00	0.17	0.98	0.29
90	KNN	97	0.97	0.96	0.96	0.18	0.98	0.31
70	NB	96	0.97	0.33	1.00	0.04	0.98	0.07
75	NB	96	0.97	0.28	1.00	0.05	0.98	0.08
80	NB	96	0.97	0.20	1.00	0.03	0.98	0.06
85	NB	96	0.97	0.19	1.00	0.03	0.98	0.05
90	NB	96	0.97	0.12	0.99	0.02	0.98	0.04
70	SVM	98	0.99	0.67	0.99	0.66	0.99	0.67
75	SVM	98	0.99	0.67	0.99	0.66	0.99	0.67
80	SVM	98	0.99	0.69	0.99	0.66	0.99	0.68
85	SVM	98	0.99	0.72	0.99	0.70	0.99	0.71
90	SVM	98	0.99	0.70	0.99	0.72	0.99	0.71

Alg-Algorithm names, Acc-overall accuracy of the classification, Prec. (yes)-Precision of Child Alive, Prec.(no)-Precision of Child Dead, Rec.(yes)-Recall of Child Alive, Rec.(no)-Recall of Child Dead, F1(yes)-F1 measure of Child Alive, F1(no)- F1 measure of Child Dead.

Figure 1 shows the accuracy, precision, recall, and F1 measure values for all the classifiers in different training sizes, while figure 2 represents the ROC curves.

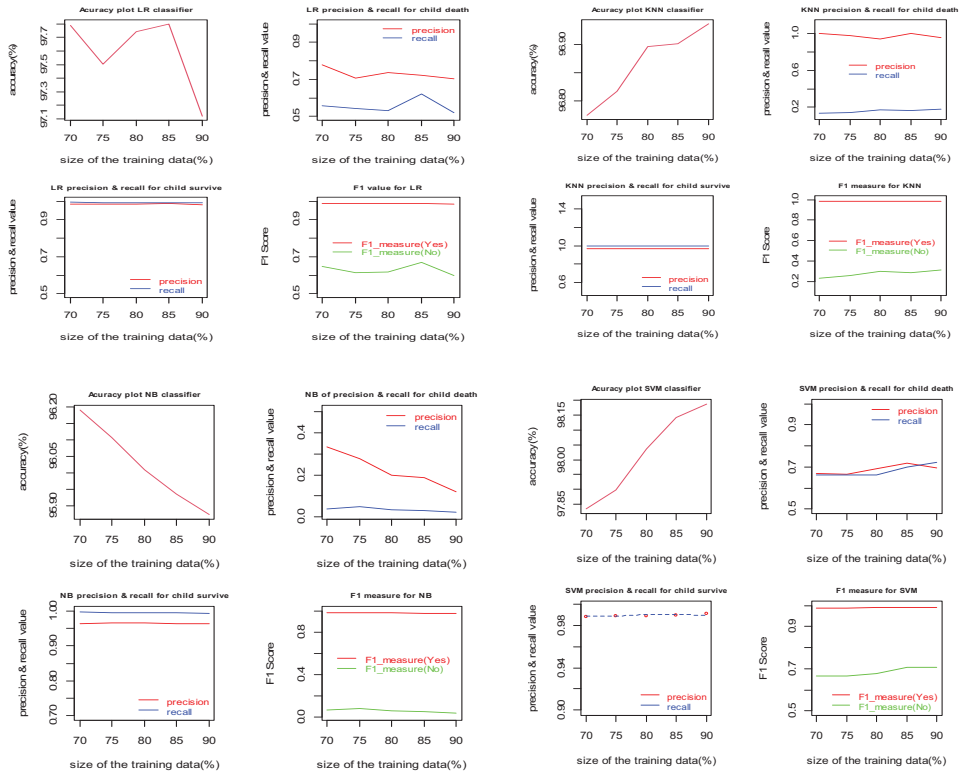


Figure :1. Precision, recall, and f1 measure graph.

The AUC values for different classifiers are

Logistic Regression AUC: 0.958

K Nearest Neighbor AUC: 0.583

Naïve Bayes AUC:0.508

Support Vector Machine AUC:0.856

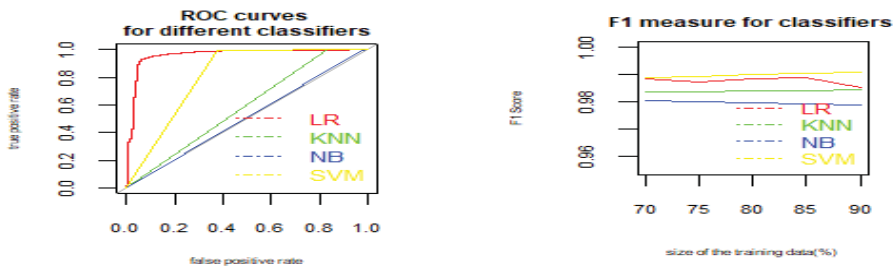


Figure : 2 Comparisons of different classifiers based on ROC curve and f1 measure

4. Discussion:

We know there is a positive relationship between family size and child survival from the past findings. In table (1), it has been revealed that child mortality is significantly associated with the Number of household members. Past studies have shown drinking water sources and their hygienic conditions have impacted child mortality (Claeson et al., 1999; Shantikumar Singh, 2014). But the present findings contradict the past results. The current findings agree with (Klaauw & Wang, 2004; Zelee, 2000). Thus, it is observed that reducing the child mortality rate due to drinking water sources is small and statistically insignificant.

For analysis, we divide the cooking fuel type into coal and electricity. Uses of electricity, LPG natural gas, Biogas, Kerosene are considered electricity, whereas others like coal, charcoal, wood, etc., are considered coal. It has been observed that the type of cooking fuel used in the household significantly affects the child mortality of that household. These findings are also agreed with (Claeson et al., 1999; Klaauw & Wang, 2004) that child mortality is lower for children in households that use a smoke-free cooking fuel than children in households using smoke produce cooking fuel (Shantikumar Singh, 2014).

Their study on child mortality (Klaauw & Wang, 2004; Shantikumar Singh, 2014) reveals that the Type of house has no significant effect on child mortality in rural India. In other words, no variation of child mortality occurs due to different types of houses. In contrast, in this study (here main roof material) and also in the study of (Sandhya, 1991), it has been found that there is a significant relationship between the type of house (here main roof material) and child dead. It is observed that the child mortality rate is associated with the type of toilet used in the households. The present study's findings of the relationship with toilet type are the same as (Klaauw & Wang, 2004) but (Zelee, 2000) results against our findings.

We agreed with the findings of various past studies that there is a strong relationship between child mortality and total children ever born (fertility). It turns out that the higher the fertility rate more significant is the risk of child death. Thus, more children born result in a higher probability of child deaths. Reducing child mortality is an important concern. Place of delivery plays a vital role in it. Both mother and infant require proper reproductive healthcare, and the amount they receive depends on the place of delivery. High mortality risk prevailed in those children delivered at home than at health care centers. Since medical professionals can instantly tackle any complication developed during childbirth, most women in a country like India who deliver at health care centers tend to have a sound socioeconomic status. Unless poor women delivered their children to a medical center only if developed some problems.

5. Conclusion

This study focuses on applying statistical analytical techniques to understand children under five survival status in North East India to bring out previously unidentified predictors of the child alive, which will be prior caution concerning people as intervention targeting. The study reveals the uses of

classification techniques like Logistic Regression, K-Nearest Neighbor, Naïve-Bayes Classifiers, and Support Vector Machine algorithm to predict child survival status. Early child mortality prediction ensures that parents adopt effective and efficient actions to improve child health, altering the children's future. Prediction can be "child alive" or "child dead." The determinant factors obtained for this study are Source of drinking water, Type of toilet facility, Main roof material, Number of household members (listed), Number of children five and under in household (de jure), Type of cooking fuel, Total children ever born, Number of living children, Birth order number, Child is twin, Sex of child and Place of delivery.

We compared the predictive performance of classifying some well-known classifiers in this context, e.g., LR, KNN, NB, and SVM. The predictive performance measures are very close for different training sizes considered in the study of each classifier. To detect the determinant for the survival and death of the under-5 child are equally important, we would aim for high precision and recall. For the LR model, the precision value of child death is around 0.2 less than that of child survived, while the recall value of child death is about 0.3 less than that of child survival.

LR and SVM models can accurately classify child survival and death as the precision line, and recall line are closed to each other for both classes. In the KNN model, a wide gap exists between the precision line and recall line for child death. The value of both precision and recall are very low in NB model for child death prediction. So we do not recommend NB and KNN for the study. Since the highest AUC value is found in the LR model, this model gives the best predictive performance compared to others considered for this study of child mortality prediction. Logistic Regression is the best classifier for predicting child survival status. Therefore, it is suggested to use for prediction to get higher accuracy and performance.

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