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Analyze the Determinants of Malnutrition in Women and Prognosticate Nutritional Status: Insights from the Bangladesh Demographic Health Survey 2022

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Abstract: Malnutrition in women is a significant public health concern and it is a serious issue in Bangladesh. The Bangladesh Demographic Health Survey (BDHS) 2022 was utilized to identify risk variables for malnourished females and fit several machine learning-based approaches to assess their nutritional status. This study included 7972 female individuals of various locations and ages. A chi-square test with a 5% significance level was used to identify possible risk variables for malnutrition in women. Naive Bayes, CART, Logistic Regression, Random Forest, Support Vector Machine, AdaBoost, Extreme Gradient Boosting, and Multilayer Perceptron; these eight machine learning-based classifiers were used to predict malnutrition in women. Summary information revealed that 48.4% of the population analyzed in this study were malnourished women. The chi-square test revealed that fourteen variables were substantially linked with malnutrition in women. Multilayer Perceptron had the highest accuracy of 0.71 for training data but it showed poor performance for the test data set. In terms of efficiency metrics such as accuracy, kappa, and F_1 scores, Random Forest outperformed the others. In comparison to the other ML algorithms tested in this study, the Random Forest technique was a significantly effective machine learning-based technique for predicting women's malnutrition in Bangladesh. The proposed approach can help identify high-risk women for malnutrition, reducing the burden on the healthcare system.

Keywords: Malnutrition, Machine Learning, AdaBoost, Cross Validation, Bangladesh

1. Introduction

Developing countries have experienced various changes, including epidemiological transitions, which refer to shifts in disease patterns, and Bangladesh is among these countries undergoing such transformations. A balanced and nutritious diet is crucial for maintaining a healthy lifestyle. A serious condition known as malnutrition arises when the body does not get the proper quantity of all the nutrients and energy it needs. Malnutrition is a serious global public health concern that raises mortality rates and the overall burden of sickness [1]. Numerous low to middle-income countries are facing significant malnutrition challenges, characterized by both a high incidence of overweight individuals and a widespread occurrence of underweight individuals [2, 3]. Bangladesh is a developing country. In Bangladesh, malnutrition is a serious problem, especially for women and children. The two main conditions that are recognized as malnutrition for women are undernutrition and being overweight or obese. Malnutrition is a global issue, and the World Health Organization (WHO) claims that 2.5 billion people aged eighteen or older will be overweight worldwide in the year 2022 as well as 390 million adults who are underweight [4]. Women and children are the main victims of this global issue. The estimation said that around 183 million women are living underweight and Bangladesh is one of the countries with the highest incidence of underweight, along with being ranked in the 25 highest countries [5]. Obesity is the extreme case of overweight and about 504 million females are the sufferers of this [5]. Even though this trend of malnutrition is decreasing day by day, it is a big concern for the world as a large number of people are still affected by malnutrition. Given that being underweight or overweight is linked to several infectious diseases, including heart disease, stroke, diabetes, cardiovascular disease, and respiratory problems [6–10]. Underweight women encounter several challenges, such as decreased work productivity and an increased risk of abortion, fetal death within the uterus, low birth weight, and infant mortality [11, 12]. According to Melchor et al., maternal obesity throughout pregnancy, birth, and the postpartum period can cause a number of challenges for both the mother and the fetus [13]. Malnutrition is caused by a number of reasons. If risk factors are not recognized early enough or are not obvious enough, malnutrition is more likely to happen. Early detection of malnutritional variables is critical to shield women from diseases that are made worse by those causes. In order to prevent malnutrition and quickly detect risk factors, action must be taken. This research is keen to get underway to predict Bangladesh's malnutrition status and determine the causes of malnutrition.

The nutritional status of an individual can reveal information about his or her health. Numerous factors have been linked to malnutrition, according to earlier research. Many statistical techniques, including univariate regression, Pearson's correlation, logistics regression, multivariate regression, and others, are proposed to determine the reasons and effects of malnourishment [3, 14–26]. Machine learning algorithms are very well-liked for precisely predicting the danger of any diseases [27]. Machine learning, which combines artificial intelligence with statistical learning, is a useful technique for finding unknown linkages or patterns [28]. In comparison to machine learning algorithms, classic statistical models have proven to be more precise in predicting outcomes for categorization problems. ML systems have been used to predict several ailments, including anemia [29–31], acute appendicitis [32], cardiovascular defect [33], covid 19 [34, 35], diabetes [28, 36–39], hypertension [40, 41], low birth weight [42–46] using a range of datasets from health surveys and demographic studies, in addition to common risk factors for the disorders. Previously, several machine learning based research studies on malnutrition have been carried out worldwide. Using machine learning approaches, Talukder and Ahammed were able to forecast the malnutrition of under five children in Bangladesh based on the data from the Bangladesh Demographic Health Survey (BDHS), 2014. The researcher concluded that, among other algorithms, Random Forest (RF) is the best [47]. Artificial Neural Network (ANN) was shown to be the most effective classifier by Shahriar et al. in their study of Malnutrition among Bangladeshi adolescents utilizing machine learning techniques [48]. Khare et al. used artificial intelligence to determine the probable link between malnutrition and the Indian Demographic Health Survey dataset from 2005-2006 [49]. According to Bitew et al., an analysis using data from the Ethiopian Demographic and Health Survey 2016 revealed that the Extreme Gradient tree algorithm produced superior results [50]. A study identified the most important factors influencing malnutrition with the use of k-nearest neighbor (kNN), Bayesian networks, Support Machine Vector (SVM), and Decision tree (DT) [51]. Based on their research, Momand et al. proposed that PART and Random Forest (RF) provide the best forecast of malnutrition [52]. Research by Rahman et al. shows that LR-RF combination models are more accurate in classifying and predicting stunted, wasted, and underweight children [53]. CART rule induction classifiers and Decision trees (DT) were among the data mining approaches utilized by Markos et al.. It is discovered that PART rule induction produced the highest accuracy results [54]. Nevertheless, little study has been done to forecast women's malnutrition using machine learning algorithms in comparison with child nutrition. Islam et al. researched BDHS 2014 data to predict malnutrition among women. The results indicated several important criteria and that the RF was the best technique to identify women's malnutrition status [6]. A study was conducted to predict the Body Mass Index (BMI) of women of childbearing age and the analysis found that SVM and kNN were the most effective algorithms for the prediction [55].

This research work is an extended part of previous work where RF was found to be the best model for predicting women's malnutrition [56]. In this research, new datasets on women are taken and four new machine learning models are conducted. Identifying potential risk factors for malnutrition in women, choosing the best-fitting models among several machine learning algorithms, and determining whether any changes arise due to new datasets and models are the main goals of the current work. These studies offer robust prediction models that enhance our comprehension of this significant health concern and provide policymakers and medical practitioners with relevant data for targeted interventions. Existing health systems can be made more capable of tracking, evaluating, and treating malnutrition by integrating machine learning prediction. This study aims to help Bangladeshi women live longer lives in healthier conditions by using its findings to assist in making informed decisions. It will also be utilized to ascertain which model best predicts the likelihood of malnourishment.

2. Materials and Methods

Ergonomic investigation will be employed in the Bangladesh Demographic Health Survey (BDHS), 2022 to look at the nutritional status of women. The preceding study, the study's background, and its goal were all covered in the last section. The approaches used to assess women's malnutrition are explained in the following section. After determining the potential risk factors using Chi-square, eight machine learning techniques were used to predict the women's likelihood of malnourishment: Naive Bayes (NB), Classification and Regression Tree (CART), Logistic Regression (LR), Random Forest (RF), Extreme Gradient Boosting (XGBoost or XGB), Support Vector Machine (SVM), Multilayer Perceptron (MLP), and AdaBoost (AB). The ethical guidelines established by the National Research Committee were adhered to in all aspects of the study's procedures involving human subjects.

2.1. Data

This study used the data from the Bangladesh Demographic and Health Survey (BDHS) 2022. According to Niport, the ninth and most recent nationwide study to assess the health and demographic conditions of women and children is the Bangladesh Demographic and Health Study (BDHS) 2022 [57].

2.2. Participants

All non-institutional housing units in Bangladesh were included in the BDHS 2022 sample, guaranteeing its national representativeness. Women between the ages of 15 and 49 who had ever been married provided information for the survey.

2.3. Data Preparation

The sample frame for the 2022 BDHS was created using a detailed list of enumeration areas (EAs) that covered the whole country and was created by the Bangladesh Bureau of Statistics for the 2011 People's Republic of Bangladesh population census. Selecting respondents for the survey involves a two-stage stratified sample technique. In the initial step, the BBS drew the sample under the guidelines given by ICF. In order to create a sample frame for the second step of household selection, Mitra and Associates then completed a thorough household listing operation in each of the chosen EAs. During the second sampling stage, a systematic sample comprising 45 households on average per EA was chosen. A series of fundamental inquiries concerning background traits and reproductive history were posed to the qualified women in each household. 30,375 residential families in total were chosen using this design (19,710 from rural and 10,665 from urban regions). These females were the representative of the all women of Bangladesh. The face-to-face interview sessions were carried out with them [57].

2.4. Outcome Variables

Body Mass Index (BMI) was recognized as the dependent variable and by the WHO, it was classified as follows: BMI $<$ 18.5 as underweight, 18.5 $\leq$ BMI $\leq$ 24.9 as normal, 25.0 $\leq$ BMI $<$ 30.0 as overweight, and BMI $>$ 30.0 as obese. kg/m^2 is the unit used for these categories [58]. The categories of underweight, overweight, and obese are combined into one for women's malnutrition.

2.5. Predictors

This study used individual, community, socioeconomic, and health service variables as predictors based on self-efficacy, the availability of datasets, and insights from previous studies [6, 24, 56, 59]. The list of selected variables with their description was given in Table 1. The wrapper method (Recursive Feature Elimination) was used to find the risk factors but this method found less than six variables as significant out of 19 variables which will mislead the prediction of models. Therefore, the filter method (Chi-square test) was utilized to find the associated determinants of malnutrition for women from these factors.

2.6. Sample Size

This study aimed to investigate the characteristics associated with female malnutrition and forecast its determinants using machine learning. Relevant factors were chosen based on this goal. 7972 people in total are chosen for further examination after missing values, odd observations, and do not know are subtracted.

2.7. Machine Learning Algorithms

This study aimed to explore characteristics associated with women's malnutrition and used machine learning to predict its determinants. Eight machine learning algorithms were employed in this study to predict malnutrition in women. The descriptions of these models are presented in below.

Naive Bayes: The foundation of Bayesian classification is the Bayes theorem, which bears Thomas Bayes' name. Bayes was a pioneer in the field of probability and decision theory during the 18th century. Class membership probabilities, such as the possibility that a given tuple belongs to a specific class, can be predicted by Bayesian classifiers [60]. The Naive Bayes model is a simple probabilistic model that can easily handle quite large amounts of data [61]. The steps of the Naive Bayes model are:

1. The Naive Bayes classifier estimates whether a tuple X belongs to a class C by optimizing the posterior probability $P(C|X)$.
2. This estimation is expressed as:

$$P(C|X) = \frac{P(X|C) \times P(C)}{P(X)}. \tag{1}$$

   where,
   (a) The *prior probability* $P(C)$,
   (b) The *likelihood* $P(X|C)$,
   (c) The *evidence* $P(X)$,
3. Since $P(X)$ is consistent across all classes, the focus is placed on $P(X|C)$ and $P(C)$ during calculations.
4. To predict the class label of X, the classifier computes $P(X_i|C_i) \times P(C_i)$ for each category C_i.
5. The class label is predicted as C_i if:

$$P(X_i|C_i)P(C_i) > P(X_j|C_j)P(C_j) \text{ for all } j \neq i. \tag{2}$$

6. The final class label corresponds to the class C_i for which $P(X_i|C_i)P(C_i)$ is maximum.

Classification and Regression Tree: Machine learning, statistics, and data mining can all benefit from decision tree (DT) learning, a type of supervised learning. Machine learning researcher J. Ross Quinlan developed the iterative decision tree method in the late 1970s and early 1980s. Moreover, Dichotomiser said ID3 [60]. Eventually, C4.5, and the Classification and Regression Tree, are ID3's successor created as a decision tree variant. In 1984, the statisticians L. Breiman, J. Friedman, R. Olshen, and C. Stone published Classification and Regression Trees (CART) under the title of the book [62]. Among the decision tree induction methods is CART. There are several steps in the DT methodology that Han et al. recommend. [60]:

1. Three parameters, the dataset, the attribute list, and the attribute selection method are used to invoke the algorithm.
2. The tree starts with a single leaf, N, which represents the tuples of training in D.
3. Leaf N will be labeled with the class if every tuple in D is a member of the same class.
4. If not, the algorithm determines the splitting criterion using the attribute selection approach.
5. Node N is given the splitting criterion, which acts as a test at the node. Beginning at node N, a branch is generated for each of the splitting criterion's conclusions.
6. The same procedure is used inductively to form a decision tree for data items for each partition so generated.
7. Recursion and partitioning are stopped when:
   (a) All itemsets in the subdivision D belong to the same class, or
   (b) There are no more features by which the tuples can be further split, or
   (c) There are no tuples for a certain branch, and partition D_j is therefore empty.
8. Finally, the decision tree is restored.

Similar to DT, CART employs the Gini index as an attribute selection technique to efficiently divide a given set of data partitions. The contamination of D, a set of training tuples or a data split, is measured by the Gini index. It measures by

$$Gini(D) = 1 - \sum_{i=1}^{n} p_i^2 \tag{3}$$

Here, p represents the tuple's probability. D. The partitioning is provided by Gini(D) as

$$Gini_A(D) = \frac{|D_1|}{|D|} \times Gini(D_1) + \frac{|D_2|}{|D|} \times Gini(D_2) \tag{4}$$

And finally,

$$\Delta Gini(A) = Gini(D) - Gini_A(D) \tag{5}$$

Logistic Regression: Logistic regression is a supervised learning technique that modifies a linear model's output to make sure it matches a binary response. It is often considered the most widely used machine learning method for binary classification. To evaluate the attribute in question, LR estimates the greatest likelihood procedure. Logistic regression is commonly used when one or more quantitative predictor variables and one or more binary answer variables are integrated and have been connected to the odds or probability of the dependent variables [63]. For example, the logistic model can be written as follows if Z_i is the number of factors:

$$p(z) = \frac{exp(\alpha_0 + \beta Z_i)}{1 + exp(\alpha_0 + \beta Z_i)}; i = 1, 2, ..., n \tag{6}$$

It also can be expressed by

$$log(\frac{p(z)}{1 - p(z)}) = exp(\alpha_0 + \beta Z_i) \tag{7}$$

$p(z)$ represents the probability that an event will occur, and $1 - p(z)$ represents the likelihood that an event won't.

Random Forest: Random Forest one of the most important algorithms is, which was developed in 2001 by L. Breiman [64]. It is a classification technique that depends on the creation of a collection of classifiers with a tree structure. The RF method constructs a decision tree from the number of feature components it selects at irregular intervals. The trees are constructed using the CART process [60]. According to Hastie et al., RF works as [65],

1. The technique first uses a training set with replacement, often called bagging, to generate bootstrapping samples Z of the total size of the training data N.
2. Recursively repeat the following steps for every tree terminal node until the minimum node size is reached in order to expand the random forest tree in the direction of the bootstrap sample:
   (a) Select m variables at random from the p variables.
   (b) From the m alternatives, select the optimal variable or split-point.
   (c) Make two daughter nodes out of every node.
3. Return the tree ensemble.

The random forest constructs a model in this manner. After that, the new or test dataset is further classified using the model.

AdaBoost: AdaBoost is a meta-algorithm for statistical classification introduced by Yoav Freund and Robert Schapire in 1995 [66]. It can be used along with many kinds of learning algorithms to enhance performance. In Boosting the output of several weak learners is computed and assembled as a weighted sum to represent the final output of the boosted classifier. Standard AdaBoost is introduced for binary classification; however, the approach can be extended to multi-class classification or even bounded ranges of real-valued outputs [65]. AdaBoost methods aggregate many weak machine-learning models into one strong classifier for output. This helps to build and mix, these models like AdaBoost techniques that combine a number of weak machine-learning models to build a strong classifier for the output. Here are the steps to build separate and combine these models:

1. For a dataset with N training data points, initialize N weights W_i for each data point with: $W_i = \frac{1}{N}$.
2. Train a weak classifier M_k, where k is the current

iteration. The weak classifier should have an accuracy greater than 0.5, meaning it performs better than a naive guess.

3. (a) Calculate the error rate, error_rate, for every weak classifier M_k on the training dataset.
   (b) Calculate the importance of each model α_k using the formula:

$$\alpha_k = \frac{1}{2} \ln \left(\frac{1 - \text{error}_k}{\text{error}_k} \right).$$

4. After applying the weak classifier M_k to the training data, update the weight assigned to each data point using the formula:

$$W_i = W_i \exp\left(-\alpha_k y_i M_k(x_i)\right),$$

where y_i is the true output and x_i is the corresponding input vector.

5. Normalize the instance weights so that they sum to 1 using the formula:

$$W_i = \frac{W_i}{\sum(W)}.$$

6. Repeat steps 2-5 for K iterations. Train K classifiers, calculate their importance and update the instance weights using the above formulas.
7. The final model $M(X)$ is an ensemble model obtained by combining the weak models weighted by their model weights.

XGBoost: XGBoost (eXtreme Gradient Boosting) is an open-source software library that provides a regularizing gradient-boosting framework. XGBoost was first released by Tianqi Chen as a beta research project under the Distributed (Deep) Machine Learning Community (DMLC) group. Tianqi Chen and Carlos Guestrin published the efficient scalable implementation of XGBoost [67]. Although the XGBoost model frequently outperforms a single decision tree in terms of accuracy, decision trees' fundamental interpretability is compromised. The Xgboost operates as follows:

1. Start with an initial prediction, often a constant value (e.g., the mean of the target variable for regression or log odds for classification).
2. (a) Define an objective function that includes:
      i. A *loss function* (l) that measures the difference between the predicted and actual values.
      ii. A *regularization term* (Ω) that controls model complexity to prevent overfitting.
   (b) The combined objective is given by:

$$\mathcal{L}(\phi) = \sum_i l(y_i, \hat{y}_i) + \sum_k \Omega(f_k),$$

   where f_k represents individual decision trees.

3. Regularization penalizes the complexity of individual trees, calculated as:

$$\Omega(f_k) = \gamma T + \frac{1}{2}\lambda \|w\|^2,$$

where T is the number of leaves, w is the weight of the leaves, and γ, λ are regularization parameters.

4. Compute the first-order derivative (*gradient*, g_i) and the second-order derivative (*Hessian*, h_i) of the loss function for each instance:

$$g_i = \frac{\partial l(y_i, \hat{y}_i)}{\partial \hat{y}_i}, \quad h_i = \frac{\partial^2 l(y_i, \hat{y}_i)}{\partial \hat{y}_i^2}.$$

5. For each tree, compute the best split by optimizing the objective function. The gain from a split is:

$$\frac{1}{2}\left[\frac{(\sum_{i\in L} g_i)^2}{\sum_{i\in L} h_i + \lambda} + \frac{(\sum_{i\in R} g_i)^2}{\sum_{i\in R} h_i + \lambda} - \frac{(\sum_{i\in P} g_i)^2}{\sum_{i\in P} h_i + \lambda}\right] - \gamma$$

where L and R are the left and right child nodes, P is the parent node, and γ is the regularization parameter.

6. Prune branches with a negative gain to prevent overfitting and ensure an optimal tree structure.
7. After fitting a tree, update the predictions for all data points:

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + \eta f_t(x_i),$$

where η is the learning rate, and $f_t(x_i)$ is the prediction from the t-th tree.

8. Repeat the above steps for a predefined number of iterations or until the improvement in the objective function stops.
9. The final model is an ensemble of all the decision trees, combined using the weights derived from the boosting process.

Multilayer Perceptron: In deep learning, multilayer perceptron (MLP) is an informal name for a modern feedforward neural network composed of multiple layers of nodes where each layer is fully connected with the next, and each node is a nonlinear activation function, which can distinguish data that is not linearly separable [68]. The first multilayered neural network trained by stochastic gradient descent, which could classify non-linearly separable pattern classes was reported by Shunichi Amari [69]. The steps that are followed by MLP are [70]:

1. The network receives the input data vector $\mathbf{x} = [x_1, x_2, \ldots, x_n]$, where n is the number of features.
2. (a) Each neuron in the hidden layer computes a weighted sum of its inputs, adds a bias term, and applies an activation function:

$$z_j = \sum_{i=1}^{n} w_{ij} x_i + b_j, \quad a_j = \phi(z_j)$$

   where w_{ij} are weights, b_j are biases, and ϕ is the activation function (e.g., sigmoid, ReLU).
   (b) This process is repeated layer by layer until the output layer, which produces predictions $\hat{\mathbf{y}}$.

3. The loss function $L(\mathbf{y}, \hat{\mathbf{y}})$ quantifies the difference between the predicted output $\hat{\mathbf{y}}$ and the true target values $\mathbf{y}$. For example, mean squared error (MSE) for regression or cross-entropy loss for classification.
4. Backpropagation:
   (a) Compute the gradient of the loss function with respect to the weights and biases in each layer using the chain rule.
   (b) Propagate the error backward through the network:
$$\frac{\partial L}{\partial w_{ij}} = \frac{\partial L}{\partial a_j} \cdot \phi'(z_j) \cdot x_i$$
   (c) Update weights and biases using the gradients and a learning rate η:
$$w_{ij}^{\text{new}} = w_{ij}^{\text{old}} - \eta \frac{\partial L}{\partial w_{ij}}$$
5. Repeat Training Steps: Perform forward propagation, loss computation, and backpropagation for multiple epochs until convergence or a stopping criterion is met (e.g., validation accuracy improvement stops).

Support Vector Machine: The support vector machine (SVM) technique is one of the most reliable and precise techniques among ML-based approaches [71]. It is a nonlinear extension of the Generalized Portrait algorithm, revolutionized via the inductive principle of structural risk minimization (SRM) [72]. One of the most researched models, SVMs were created at AT&T Bell Laboratories and are based on the statistical learning frameworks of VC theory put out by Chervonenkis (1974) and Vapnik (1982, 1995) [73]. The steps followed by SVM are:

1. *Input the data:* Begin with a dataset $\{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$, where x_i represents the feature vector, and $y_i \in \{-1, +1\}$ represents the class labels.
2. *Define the hyperplane:* SVM aims to find the optimal hyperplane that separates the data points belonging to different classes. The hyperplane is represented as:
$$w^T x + b = 0$$
   where w is the weight vector and b is the bias.
3. *Maximize the margin:* The margin is the distance between the hyperplane and the closest data points (support vectors). The optimization problem is formulated to maximize this margin:
$$\text{Minimize: } \frac{1}{2}\|w\|^2$$
   Subject to:
$$y_i(w^T x_i + b) \geq 1, \quad \forall i$$
4. *Handle non-linearly separable data (Soft Margin):* For non-linearly separable data, introduce slack variables ξ_i to allow some misclassification:
$$\text{Minimize: } \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} \xi_i$$
   Subject to:
$$y_i(w^T x_i + b) \geq 1 - \xi_i, \quad \xi_i \geq 0, \quad \forall i$$
5. *Kernel trick for high-dimensional data:* To handle non-linear decision boundaries, SVM uses kernel functions to map the data to a higher-dimensional space:
$$K(x_i, x_j) = \phi(x_i)^T \phi(x_j)$$
   Common kernels include:
   (a) Linear: $K(x_i, x_j) = x_i^T x_j$
   (b) Polynomial: $K(x_i, x_j) = (x_i^T x_j + 1)^d$
   (c) Gaussian RBF: $K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right)$
6. *Solve the optimization problem:* Use the Lagrange multiplier method to solve the optimization problem, leading to the dual form:
$$\text{Maximize: } \sum_{i=1}^{n} \alpha_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j K(x_i, x_j)$$
   Subject to:
$$\sum_{i=1}^{n} \alpha_i y_i = 0, \quad 0 \leq \alpha_i \leq C, \quad \forall i$$
7. *Make predictions:* The decision function for a new input x is:
$$f(x) = \text{sign}\left(\sum_{i=1}^{n} \alpha_i y_i K(x_i, x_j) + b\right)$$
   where α_i are the Lagrange multipliers, and b is the bias term.

2.8. Algorithm Assessment

Evaluation measures including accuracy (Ac), recall (Re), precision (Pr), Cohen's Kappa, F_1 score, roc curve, and AUC are used in this study to assess these five algorithms. Additionally, k-fold cross-validation methods are employed to ascertain these performance metrics. True positive (TP), true negative (TN), false positive (FP), and false negative (FN) classifiers are all included in the confusion matrix. It is feasible to quantify these assessment parameters by this matrix [74].

Accuracy is the basis for evaluating the effectiveness of any forecasting method. It determines the percentage of accurately forecasted total data points. 1.0 represents the highest possible accuracy, and 0.0 represents the lowest. It can be easily calculated by simply dividing the total number of forecasts by the number of accurately forecasted. It can also be stated as,

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{8}$$

This study compiled the best levels of accuracy achieved through different ML algorithms.

Recall relates to how well the model can determine which cases are true positives. Sensitivity and true positive rate are other names for it. The ratio of the total number of positive features to the number of true-positive results which also includes false positives is used to calculate sensitivity. The following formula can be used to determine recall mathematically:

$$Recall = \frac{TP}{TP + FN} \tag{9}$$

Precision is used to describe a model's capacity to forecast whether or not there would be positive examples among those that anticipated positive. It is also known as positive predictive value. In the event of a positive test result, this characteristic can predict the likelihood that a person would be a true positive case. Precision may be calculated using

$$Precision = \frac{TP}{TP + FP} \tag{10}$$

The F_1 score is a way of measuring a test's accuracy. The precision and recall of the test determine it. The frequency of accurate predictions across all data is determined by the F_1 score. The F_1 score is determined by taking the harmonic mean of a model's precision and recall. This can be measured using the equation below.

$$F_1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{11}$$

Cohen's Kappa statistic is a more efficient method for handling multi-class and misaligned class issues. It is the proportion of understanding between the actual and expected classifications in a collection of data. A single classifier or several classifiers together can be evaluated using the Kappa statistic. According to the statistics, 0 indicates no agreement, 0 to 0.20 indicates mild agreement, 0.21 to 0.40 indicates reasonable agreement, 0.41 to 0.60 indicates moderate agreement, 0.61 to 0.80 indicates substantial agreement and 0.81 to 1 indicates nearly perfect agreement [75]. It is measurable by;

$$Kappa = \frac{Accuracy - Random\ Accuracy}{1 - Random\ Accuracy} \tag{12}$$

where, Random Accuracy is the ratio between [(TN+FP) (TN+FN) + (FN+TP) (FP+TP)] and [(TP+FP+TN+FN) (TP+FP+TN+FN)]

The *ROC curve* is another name for the operating characteristic curve of the receiver. It is a graph that shows the performance of a classification model at every classification level. Two parameters are shown by this curve: the true positive rate and the false positive rate. The area beneath the ROC curve is referred to as AUC. AUC determines the two-dimensional area beneath the whole ROC curve. By comparing two models, AUC evaluates the effectiveness of the same model across a range of thresholds.

Table 1. *Factors classification of malnutrition used in this study.*

Categorical Factors	Description	Class level
Age	Age in group	15-24 (A1), 25-34 (A2), 35-49 (A3)
Residence	Type of place of residence	Urban, Rural
Region	Division	South (Sou): Barisal, Chittagong, Dhaka, Khulna; North (Nor): Mymensingh, Rajshahi, Rangpur, Sylhet
Education	Highest educational level	No education, Primary, Secondary, Higher
Currently working	Respondent currently working	No, Yes
Currently breastfeeding	Breastfeeding status	No, Yes
Contraceptive Method	Current use by method type	No and Folkloric Method, Modern Method, Traditional Method
Age at 1st Birth	Respondent Age at 1st Birth	$<$ 18 (LT18), $\geq$ 18 (GE18)
Birth in last 5 years	Number of birth in last 5 years	1-2, 3-4
Currently pregnant	Pregnancy status	No, Yes
Children ever born	Number of children ever born	1-2, 3-4, 5 or more
Sex of Household Head	Sex of Household Head of Respondent	Male, Female
No of Household Members	Number of household members	$<$ 5 (LT5), $\geq$ 5 (GE5)
Wealth index	Wealth index	Poor, Middle, Rich
Partner Education	Husband education level	No education, Primary, Secondary, Higher
Accessing to healthcare	Accessing to healthcare of Respondent	No problem, Problem
Media Exposure		No, Yes
Water Source	Source of drinking water	Safe, Unsafe
Toilet facility	Type of toilet facility	Hygienic, Unhygienic

3. Results

Table 2. *Background and demographic characteristics of the study.*

Name	Category	Observations	Percentage
Nutritional Status (NS)	Malnutrition	3857	48.4
	Normal	4115	51.6
Age (AG)	15-19 (A1)	1420	17.8
	20-34 (A2)	2955	37.1
	35-49 (A2)	3597	45.1
Residence (RE)	Urban (Ur)	2757	34.6
	Rural (Ru)	5215	65.4
Region (RG)	South (SOU)	4252	53.3
	North (NOR)	3720	46.7
Education (ED)	No Education (Ne)	1130	14.2
	Primary (Pri)	2211	27.7
	Secondary (Se)	3560	44.7
	Higher (Hi)	1071	13.4
Currently Working (CW)	No (N)	5303	66.5
	Yes (Y)	2669	33.5
Currently Breastfeeding (BF)	No (N)	6192	77.7
	Yes (Y)	1780	22.3
Contraceptive Method (CP)	No (N)	2453	30.8
	MM (M)	4675	58.6
	TM (T)	844	10.6
Age at 1st Birth (FB)	$<$ 18 (LT18)	3781	47.4
	$\geq$ 18 (GE18)	4191	52.6
Birth in last 5 years (B5Y)	None	4553	57.1
	1-2	3397	42.6
	3 or more	22	0.3
Currently Pregnant (CPr)	No (N)	7665	96.1
	Yes (Y)	307	3.9
Children Ever Born (CH)	1-2	4753	59.6
	3-4	2675	33.6
	5 or more	544	6.8
Sex of Household Head (HH)	Male	7026	88.1
	Female	946	11.9
No of Household members (NH)	$<$ 5 (LT5)	2372	29.8
	$\geq$ 5 (GE5)	5600	70.2
Wealth Index (WI)	Poor (P)	2997	37.6
	Middle (M)	1610	20.2
	Rich (R)	3365	42.2
Partner Education (PE)	No education (NE)	1880	23.6
	Primary (Pri)	2331	29.2
	Secondary (Sec)	2491	31.2
	Higher (High)	1270	15.9
Accessing to Healthcare (HC)	Prob	4873	61.1
	Nprob	3099	38.9
Media Exposure (MD)	No (N)	3326	41.7
	Yes (Y)	4646	58.3
Water Source (DWS)	Safe (SF)	7810	98.0
	Unsafe (USF)	162	2.0
Toilet Facility (TF)	Hygienic (HY)	6648	83.4
	Unhygienic (UHY)	1324	16.6

The study's premise is to envision Bangladeshi women suffering from malnutrition. The Bangladesh Demographic and Health Survey (BDHS, 2022) provided the data for this investigation. BMI is selected as the explanatory variable because it is a measurement that uses height and weight to determine if a person is fit and active. 19 exposure factors are taken into account based on previous research [6, 24, 56, 59]. The study is carried out with a total of 7972 participants from BDHS, 2022 after eliminating all unnecessary data. These women were divided into four categories based on their BMI: underweight, normal, overweight, and obese. It is possible to treat overweight and obese people in the same way. The women's BMI indicates their nutritional state. Table 2 showed the current nutritional status of the women who were chosen for the research along with the other exposures that were chosen. Approximately 50% of the population is in good nutritional status. For this study, underweight and overweight have been integrated into one category of malnutrition. Therefore, there are two groups for the experimental variable in this study: normal and malnutrition. 3857 malnourished women, or 48.40 percent of the population, are included in the data set. Conversely, 51.60 percent of the study data set, which comprises 4115 women, are normal. In Table 2, the variables that are regarded as risk factors are also compiled. The research identifies 19 risk variables. The respondents came from two different sorts of residences: urban and rural. The women are mostly from rural areas. Approximately 5215 women, or 65.40 percent of the total population, are from rural areas. There are eight divisions in Bangladesh. The study combines the distinctions into two categories, north and south. Barisal, Khulna, Dhaka, and Chattagram are located in the south, whereas Mymensingh, Rajshahi, Rangpur, and Sylhet are located in the north.

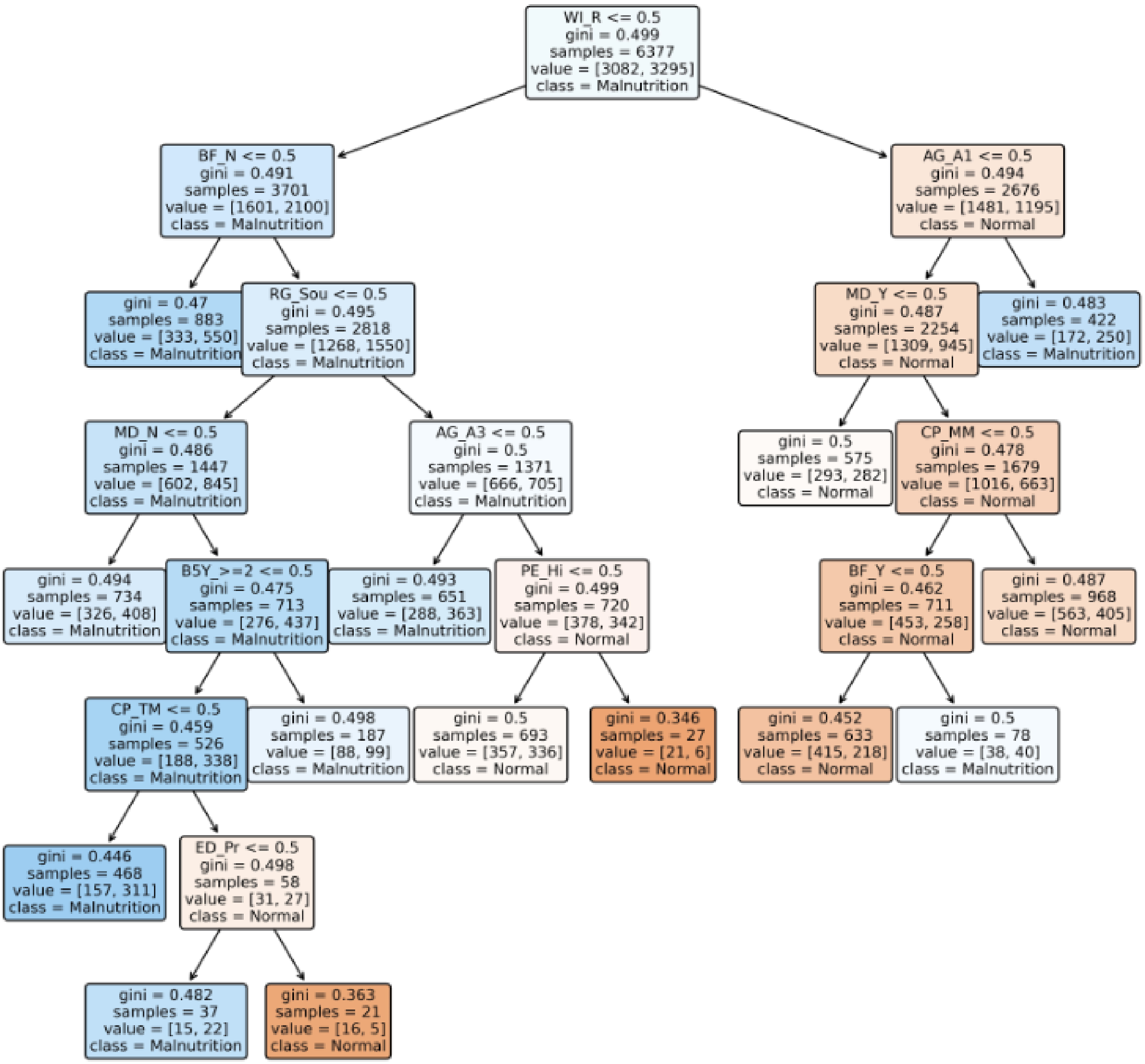

__Figure 1.__ CART model to predict malnutrition based on Bangladesh Demographic Health Survey-2022.

Table 3. *Association between important factors and nutritional status among Observed (O_i) and Expected (E_i) for women from BDHS-2022.*

Factors	**Category**	**Malnutrition $O_i(E_i)$**	**Normal $O_i(E_i)$**	**Chi-square (p-value)**
Age (AG)	15-19 (A1)	571(687.0)	849(733.0)	52.4 ($< 0.001^*$)
	20-34 (A2)	1432(1429.7)	1523(1525.3)	
	35-49 (A2)	1854(1740.3)	1743(1856.7)	
Residence (RE)	Urban (Ur)	1503(1333.9)	1254(1423.1)	63.5 ($< 0.001^*$)
	Rural (Ru)	2354(2523.1)	2861(2691.9)	
Region (RG)	South	2164(2057.2)	2088(2194.8)	23.0 ($< 0.001^*$)
	North	1693(1799.8)	2027(1920.2)	
Education (ED)	No Education (NE)	474(546.7)	656(583.3)	36.0 ($< 0.001^*$)
	Primary (Pr)	1036(1069.7)	1175(1141.3)	
	Secondary (Se)	1771(1722.4)	1789(1837.6)	
	Higher (Hi)	576(518.2)	495(552.8)	
Currently Working (CW)	No (N)	2638(2565.7)	2665(2737.3)	11.80 (0.001^*)
	Yes (Y)	1219(1291.3)	1450(1377.7)	
Currently Breastfeeding (BF)	No (N)	3110(2995.8)	3082(3196.2)	37.8 ($< 0.001^*$)
	Yes (Y)	747(861.2)	1033(918.8)	
Contraceptive Method (CP)	No (N)	1254(1186.8)	1199(1266.2)	28.8 ($< 0.001^*$)
	MM (M)	2148(2261.9)	2527(2413.1)	
	TM (T)	455(408.3)	389(435.7)	
Age at 1st Birth (FB)	≥ 18 (GE18)	1977(2027.7)	2214(2163.3)	5.2 (0.023^*)
	< 18 (LT18)	1880(1829.3)	1901(1951.7)	
Birth in last 5 years (B5Y)	No	2310(2202.8)	2243(2350.2)	30.0 ($< 0.001^*$)
	$1-2$	1543(1643.5)	1854(1753.5)	
	$3-4$	4(10.6)	18(11.4)	
Currently Pregnant (CPr)	No (N)	3700(3708.5)	3965(3956.5)	0.97 (0.324)
	Yes (Y)	157(148.5)	150(158.5)	
Children Ever Born (CH)	$1-2$	2309(2299.6)	2444(2453.4)	4.3 (0.115)
	$3-4$	1308(1294.2)	1367(1380.8)	
	≥ 5	240(263.2)	304(280.8)	
Sex of Household Head (HH)	Male (M)	3378(3399.3)	3648(3626.7)	2.8 (0.140)
	Female (F)	479(457.7)	467(488.3)	
No of Household members (NH)	≥ 5	2741(2709.4)	2859(2890.6)	2.4 (0.121)
	< 5	1116(1147.6)	1256(1224.4)	
Wealth Index (WI)	Poor (P)	1239(1450.0)	1758(1547.0)	145.0 ($< 0.001^*$)
	Middle (M)	731(778.9)	879(831.1)	
	Rich (R)	1887(1628.0)	1478(1737.0)	
Partner Education (PE)	No education (NE)	840(909.6)	1040(970.4)	51.2 ($< 0.001^*$)
	Primary (Pri)	1048(1127.8)	1283(1203.2)	
	Secondary (Sec)	1268(1205.2)	1223(1285.8)	
	Higher (High)	701(614.4)	569(655.6)	
Accessing to Healthcare (HC)	Problem (Prob)	2296(2357.6)	2577(2515.4)	8.0 (0.005^*)
	Not Problem (Nprob)	1561(1499.4)	1538(1599.6)	
Media Exposure (MD)	No (N)	1427(1609.2)	1899(1716.8)	68.6 ($< 0.001^*$)
	Yes (Y)	2430(2247.8)	2216(2398.2)	
Water Source (DWS	Safe (SF)	3766(3778.6)	4044(4031.4)	4.0 (0.045^*)
	Unsafe (USF)	91(78.4)	71(83.6)	
Toilet Facility (TF)	Hygienic (HY)	3310(3216.4)	3338(3431.6)	31.8 ($< 0.001^*$)
	Unhygienic (UHY)	547(640.6)	777(683.4)	

There are 4252 people from the south and 3720 people from the north. Every respondent is a married woman between the ages of 15 and 49. Three categories have been established for this age range. A1 is between 15 and 24, A2 is between 25 and 34, while A3 is between 35 and 49. About 37.10 and 45.10 percent of the women belong to the A2 and A3 groups, while the A1 group comprises fewer women. Many people polled are from wealthy households. In all, 3365 women belong to the wealthy class, whereas 1610 and 2997 women belong to the middle class and lower classes. Not every study participant has a high level of education. A higher degree of education was attained by 13.40% of women. The great majority of women finished their primary and secondary education. Approximately 34% of the women in the survey are employed in various professions at the moment. At the time of the poll, a significant portion of women were not pregnant. Approximately 22.30 percent of moms were nursing their children. Since all of the women are married, there are more of them with kids. The variable "children ever born," which is divided into three categories, represents the number of children that women have. Some of them fall under the group which has 1 or 2 children and this category includes the greatest number of women approximately 4753. About 2675 women belong to the category of women who have 3 or 4 children. Few women had 5 or more children. About half of the women gave birth to their first child under the age of 18. About one-third of the women did not give birth to any children, according to the factor of birth in the previous five years. In the previous five years, 42.60 percent of women gave birth to more than two children, and the smallest percentage of women less than 1% had more than three children within the previous five years. Modern contraceptive methods were highly popular among the respondents. Around 59% of women used modern contraception methods while only 10% were using traditional methods. 70 percent of households had members 5 or more and the majority of the families had male heads of household in this study. Approximately 23.6% of women across all respondents have illiterate partners. A significant number of women have partners who have finished primary or secondary school. Additionally, 15.90 percent of women have a partner with higher education. Accessing the medical facility was difficult for about 61% of women. Around 60 percent of women in this study were familiar with media exposure while 40 percent of women did not have access to social media. Approximately 98 percent of the study's respondents get their water from a reliable source. The great majority of those surveyed use clean restrooms. Out of the entire population, 6648 women have access to sanitary restrooms; only 1324 women lack such facilities.

Identification of risk factors of malnutrition using the filter method: As previously mentioned, several variables have been used to forecast the rate of malnutrition among Bangladeshi women based on earlier research. The Chi-square (χ^2) test is used to determine whether these variables are significant. Five percent was used as the significance criterion for the Chi-square test. The $p\text{-}value$ of each variable is used to evaluate the outcome. Table 3 displays the expected frequencies of the categories along with the results of the Filter technique Chi-square test of the variables with p-values. The majority component has a high (χ^2) value with a p-value < 0.001. Age at 1st birth and water source had the $p\text{-}value$ of 0.023 and 0.045, respectively. As these values were less than 0.05, therefore these two exposures were significant to women's malnutrition. Four variables in this study were not significant, and these were Cpr, CH, HH, and NH. Thus, out of the 19 variables selected for the study, 15 are significant at the 5 percent significance level. This study used these 15 variables as risk factors for women's malnutrition in Bangladesh for BDHS, 2022, in order to predict the malnutrition of women using six machine learning (ML)-based algorithms and evaluate their effectiveness.

Table 4. *The confusion matrix for various models - CART, XGB, RF, NB, SVM, MLP, and LR in predicting malnutrition in Bangladesh based on BDSH-2022 Data.*

Model	Category		Predicted (Training)		Predicted (Test)	
			Malnutrition	Normal	Malnutrition	Normal
CART	Actual	Malnutrition	1665	1417	422	353
		Normal	1252	2043	322	498
XGB	Actual	Malnutrition	1645	1437	410	365
		Normal	1064	2231	293	527
RF	Actual	Malnutrition	1740	1342	428	347
		Normal	1139	2156	295	525
NB	Actual	Malnutrition	1713	1369	436	339
		Normal	1335	1960	316	504
SVM	Actual	Malnutrition	1481	1601	406	369
		Normal	1195	2100	283	537
MLP	Actual	Malnutrition	2100	982	385	390
		Normal	884	2411	380	440
LR	Actual	Malnutrition	1607	1475	412	363
		Normal	1165	2130	286	534
AB	Actual	Malnutrition	1610	1472	413	362
		Normal	1167	2128	287	533

Performances of the machine learning methods: The present research has utilized eight different machine learning algorithms for the classification of the women in the dataset as malnourished. These eight machine learning techniques include Classification and Regression Tree, Extreme Gradient Boosting, Random Forest, Naive Bayes, Support Vector Machine, Multilayer Perceptron, Logistic Regression, and AdaBoost. The training and test datasets were separated from the entire dataset. 25% of the data was chosen as test data (test data set 1993), while 75% of the data was used as training data (training data set 5979).

Classification and Regression Tree (CART): The classification and regression tree (CART) is a decision tree that predicts women's nutritional status. The decision tree for the measured variable was displayed in Figure 1. The WI factor was used to create the tree's first node, and the Gini index was used to divide the factors. Each Gini index outcome generated a branch from the original node. This tree was used to make predictions for both test and training data, and its performance was evaluated. Table 4 represented the confusion matrix of all models. The confusion matrix demonstrates that CART can correctly classify 2043 people as healthy and 1665 as malnourished based on training data, and 498 people as healthy and 422 as malnourished based on test data. The prediction outcome employing the efficacy levels of classification and regression trees for both the test and training data is shown in Table 5. The training data and test data's accuracy was 0.58, meaning that, about the total number of forecasts generated, the model made accurate predictions 58% of the time. Accordingly, the model's precision values for training and test data were 0.58, respectively. Additionally, the CART algorithm's recall for the training and test data sets was also 0.58, respectively. The F_1 score of CART, which is 58 times out of 100 for the entire training and test data sets, respectively, showed the model's ability to detect positive normal cases while retaining accuracy with the samples it captured.

Extreme Gradient Boosting: Based on training data, XGBoost can accurately categorize 2231 individuals as healthy and 1645 as malnourished; based on test data, it can correctly classify 527 individuals as healthy and 410 as malnourished, as shown by the confusion matrix in Table 4. Table 5 displayed the prediction result and the accuracy of the training and test data was 0.61 and 0.59, which indicates that the model produced accurate predictions 61% and 59% of the time, relative to the total number of forecasts generated. Consequently, the precision and recall values of the model for both training and test data were 0.61 and 0.59, respectively. With a F_1 score of 60 times out of 100 for both the training and test data sets, respectively, XGBoost demonstrated that the model could accurately identify positive normal instances in the samples it collected.

Random Forest: The bagging approach Random Forest is utilized to fit the model for predicting the nutritional condition of Bangladeshi women in this study. The three hundred and eighteen decision trees are constructed using the square root of total randomly selected variables to predict malnutrition. Also, a max depth of 6 along with minimum samples split 3 and minimum samples leaf 9 was used for the random forest as the obtained tuning parameters. The confusion matrix in Table 4 showed that RF can correctly classify 2156 people as healthy and 1740 as malnourished based on training data, and 525 people as healthy and 428 as malnourished based on test data. The prediction result was shown in Table 5, and the accuracy of the training and test data was 0.61 and 0.60, respectively. This means that, to the total number of forecasts made, the model provided accurate predictions 61% and 60% of the time. Consequently, for both training and test data, the model's precision and recall values were 0.60 and 0.56 for training and 59 and 55 for test data, respectively. For the whole training and test data sets, RF's F_1 score was 58 and 57 times out of 100, respectively, indicating the model's ability to detect positive normal cases while retaining accuracy with the samples it obtained.

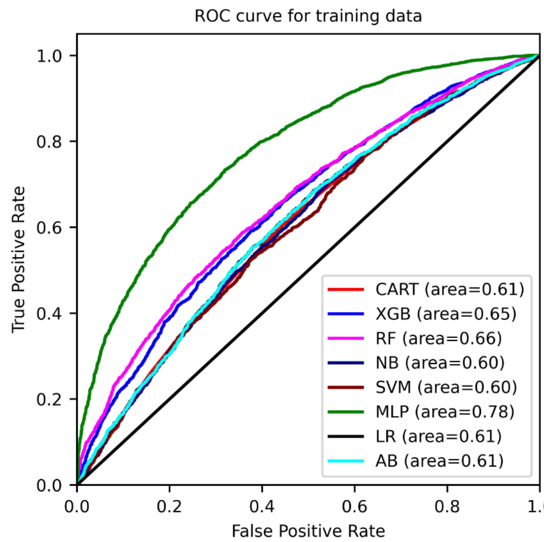

Figure 2. *ROC curve of machine learning models to predict malnutrition of women using the training dataset.*

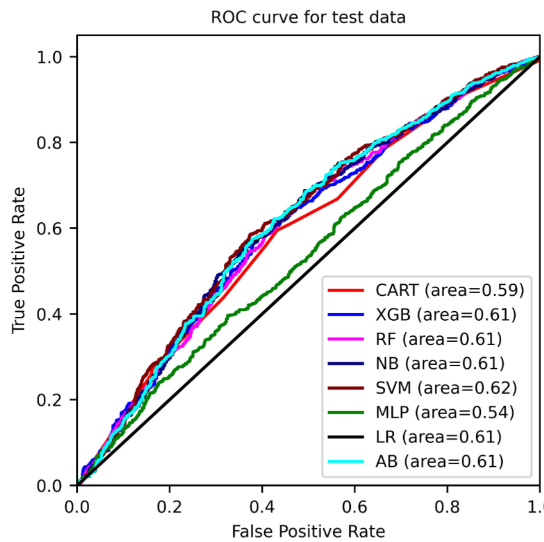

Figure 3. *ROC curve of machine learning models to predict malnutrition of women using the test dataset.*

Naive Bayes: The Naive Bayes model employed the probability of class labels 'No' or 'Yes' for malnutrition along with the likelihood that a given tuple belonged to a specific class. Table 4 displayed the predictive outcomes for both training and test data using the Naive Bayes performance settings. NB can recognize 1713 patients as malnourished and 1960 as normal, according to the confusion matrix based on training data. With a training data accuracy of 0.58, the model was correct 58% of the time out of all the predictions it generated. The test data, however, had an accuracy of 0.59. For both training and test data, the model's precision was 0.58 and 0.59, respectively. The model can collect positive normal instances 58 and 59 percent of the time, according to F_1 score, while still retaining accuracy with the examples it does capture over the whole training and test data set.

Table 5. *The classification report for the machine learning models - CART, XGB, RF, NB, SVM, MLP, and LR to predict malnutrition based on Bangladesh Demographic Health Survey-2022.*

Model	Name	Training Data			Test Data		
		Precision	Recall	F_1-score	Precision	Recall	F_1-score
CART	Malnutrition	0.57	0.54	0.56	0.57	0.54	0.56
	Normal	0.59	0.62	0.60	0.59	0.61	0.60
	Macro average	0.58	0.58	0.58	0.58	0.58	0.58
	Weighted average	0.58	0.58	0.58	0.58	0.58	0.58
	Accuracy	0.58			0.58		
XGB	Malnutrition	0.61	0.53	0.57	0.58	0.53	0.55
	Normal	0.61	0.68	0.64	0.59	0.64	0.62
	Macro average	0.61	0.61	0.60	0.59	0.59	0.59
	Weighted average	0.61	0.61	0.61	0.59	0.59	0.59
	Accuracy	0.61			0.59		
RF	Malnutrition	0.60	0.56	0.58	0.59	0.55	0.57
	Normal	0.62	0.65	0.63	0.60	0.64	0.62
	Macro average	0.61	0.61	0.61	0.60	0.60	0.60
	Weighted average	0.61	0.61	0.61	0.60	0.60	0.60
	Accuracy	0.61			0.60		
NB	Malnutrition	0.56	0.56	0.56	0.58	0.56	0.57
	Normal	0.59	0.59	0.59	0.60	0.61	0.61
	Macro average	0.58	0.58	0.58	0.59	0.59	0.59
	Weighted average	0.58	0.58	0.58	0.59	0.59	0.59
	Accuracy	0.58			0.59		
SVM	Malnutrition	0.55	0.48	0.51	0.59	0.52	0.55
	Normal	0.57	0.64	0.60	0.59	0.65	0.62
	Macro average	0.56	0.56	0.56	0.59	0.59	0.59
	Weighted average	0.56	0.56	0.56	0.59	0.59	0.59
	Accuracy	0.56			0.59		
MLP	Malnutrition	0.70	0.68	0.69	0.50	0.50	0.50
	Normal	0.71	0.73	0.72	0.53	0.54	0.53
	Macro average	0.71	0.71	0.71	0.52	0.52	0.52
	Weighted average	0.71	0.71	0.71	0.52	0.52	0.52
	Accuracy	0.71			0.52		
LR	Malnutrition	0.58	0.52	0.55	0.59	0.53	0.56
	Normal	0.59	0.65	0.62	0.60	0.65	0.62
	Macro average	0.59	0.58	0.58	0.59	0.59	0.59
	Weighted average	0.59	0.59	0.58	0.59	0.59	0.59
	Accuracy	0.59			0.59		
AB	Malnutrition	0.58	0.52	0.55	0.59	0.53	0.56
	Normal	0.59	0.65	0.62	0.60	0.65	0.62
	Macro average	0.59	0.58	0.58	0.59	0.59	0.59
	Weighted average	0.59	0.59	0.58	0.59	0.59	0.59
	Accuracy	0.59			0.59		

Table 6. The k-fold validation results for test and training data for the machine learning models - CART, XGB, RF, NB, SVM, MLP, and LR to predict malnutrition based on the Bangladesh Demographic Health Survey-2022.

Model	k	Training data				Test data			
		Accuracy	Precision	Recall	F_1 score	Accuracy	Precision	Recall	F_1 score
CART	05	0.5859	0.5873	0.5821	0.5778	0.5665	0.5684	0.5625	0.5508
	10	0.5826	0.5840	0.5793	0.5751	0.5415	0.5447	0.5391	0.5207
	15	0.5819	0.5827	0.5787	0.5751	0.5498	0.5521	0.5474	0.5377
	20	0.5816	0.5825	0.5787	0.5753	0.5485	0.5521	0.5470	0.5336
XGB	05	0.6104	0.6104	0.6082	0.6073	0.5544	0.5561	0.5522	0.5443
	10	0.6049	0.6049	0.6026	0.6016	0.5514	0.5547	0.5493	0.5402
	15	0.6049	0.6050	0.6025	0.6013	0.5411	0.5445	0.5387	0.5306
	20	0.6038	0.6039	0.6014	0.6002	0.5380	0.5376	0.5357	0.5229
RF	05	0.6140	0.6135	0.6128	0.6127	0.5570	0.5591	0.5558	0.5492
	10	0.6095	0.6090	0.6081	0.6078	0.5536	0.5580	0.5524	0.5430
	15	0.6089	0.6083	0.6075	0.6074	0.5430	0.5471	0.5418	0.5343
	20	0.6081	0.6076	0.6068	0.6066	0.5352	0.5356	0.5342	0.5199
NB	05	0.5818	0.5812	0.5810	0.5810	0.5711	0.5760	0.5703	0.5617
	10	0.5810	0.5804	0.5802	0.5802	0.5697	0.5756	0.5691	0.5607
	15	0.5809	0.5803	0.5801	0.5801	0.5664	0.5760	0.5656	0.5569
	20	0.5809	0.5803	0.5801	0.5801	0.5631	0.5665	0.5624	0.5477
SVM	05	0.5682	0.5675	0.5658	0.5642	0.5682	0.5685	0.5658	0.5626
	10	0.5682	0.5673	0.5657	0.5642	0.5679	0.5697	0.5653	0.5606
	15	0.5682	0.5673	0.5657	0.5643	0.5679	0.5714	0.5655	0.5606
	20	0.5682	0.5674	0.5657	0.5643	0.5679	0.5689	0.5654	0.5567
MLP	05	0.7061	0.7060	0.7055	0.7056	0.5225	0.5219	0.5213	0.5183
	10	0.6921	0.6927	0.6913	0.6910	0.5120	0.5119	0.5115	0.5078
	15	0.6924	0.6923	0.6917	0.6917	0.5041	0.5037	0.5033	0.5014
	20	0.6926	0.6925	0.6922	0.6921	0.5056	0.5046	0.5047	0.5004
LR	05	0.5885	0.5879	0.5865	0.5858	0.5709	0.5765	0.5687	0.5580
	10	0.5871	0.5865	0.5851	0.5843	0.5633	0.5684	0.5616	0.5521
	15	0.5870	0.5864	0.5850	0.5843	0.5574	0.5627	0.5554	0.5470
	20	0.5868	0.5862	0.5848	0.5840	0.5529	0.5549	0.5509	0.5359
AB	05	0.5881	0.5874	0.5861	0.5855	0.5709	0.5764	0.5687	0.5581
	10	0.5869	0.5863	0.5849	0.5842	0.5637	0.5687	0.562	0.5527
	15	0.5868	0.5862	0.5848	0.5841	0.5567	0.5619	0.5547	0.5466
	20	0.5867	0.5861	0.5847	0.5839	0.5524	0.5544	0.5504	0.5354

Support Vector Machine: Support Vector Machine is a supervised machine learning algorithm that creates an ideal hyperplane or decision boundary to divide input points into discrete classes. Using the SVM performance parameters, the predictive results for both training and test data were shown in Tables 4 and 5. The confusion matrix showed that SVM can recognize 1481 patients as malnourished and 2100 as normal based on training data. The model's accuracy of the training data was 0.56, meaning that it was correct 56% of the time out of all the predictions it made. However, the accuracy of the test data was 0.59. The precision of the model was 0.56 for training data and 0.59 for test data. The F_1 score shows that the model collects positive normal cases 56 and 59 percent of the time, while maintaining accuracy with the examples it does detect across the training and test data set.

Multilayer Perceptron: The Multilayer Perceptron (MLP) is a type of feedforward artificial neural network that uses nonlinear activation functions to translate input data to outputs across several layers of neurons. The confusion matrix in Table 4 shows that MLP can properly classify 499 individuals as healthy and 388 as malnourished based on test data, and 2997 individuals as healthy and 2765 as malnourished based on training data. The accuracy of the training and test data was 0.71 and 0.52, respectively, and the prediction result was displayed in Table 5. This indicates that the model produced correct predictions as well as recall and F_1 were 90% and 56% of the time, respectively, compared to the total number of forecasts made.

Logistic Regression: Malnutrition in women was predicted using logistic regression fitted to training data with the reference category 'No'. Using Logistic Regression, Tables 4 and 5 displayed the prediction performance for both the test and training data. LR has an accuracy of 0.59 in classifying 1607 women as malnourished and 2130 women as normal for training data. With LR's accuracy of 0.59 for the test data set as well, 534 can be classified as normal, while 412 can be classified as malnourished. The precision, recall, and F_1 scores were equal for both the training and test data sets.

AdaBoost: AdaBoost is an ensemble learning method that iteratively combines several weak classifiers to concentrate more on cases that were incorrectly classified, hence producing a strong classifier. Tables 4 and 5 represented the confusion matrix and assessment of the model. The model fitted with the training data set correctly classified 1610 women as malnourished and 2128 women as normal. For the test data set, 533 people were recognized by the model as normal in comparison to 413 women having malnutrition. The accuracy, recall, precision, and F_1 showed the same value of 0.59 for both training and test data sets.

The ROC curve along with the AUC of the fitted models was presented in Figures 2 and 3. The ROC curve of the models for the training data set which was presented in Figure 2 displayed that RF had the highest area under a curve of 0.97. MLP was the second highest having a 0.78 area under the curve. Other models had an AUC of around 0.60 to 0.65. On the contrary, the test data set had the least AUC values of 0.56 and 0.54 for both RF and MLP, separately. The SVM had the highest AUC value of 0.62 with AB, LR, NB, and XGB with the second highest of 0.61 AUC value.

Evaluation of the efficacy of machine learning methods: NB, CART, LR, RF, XGBoost, MLP, SVM, and AB were the eight machine learning algorithms used to predict the malnutrition of women from BDHS, 2022. Out of the total data set, 75% of the algorithms were trained using fixed data. However, one training data set did not assess the outcome since biases and variability would be introduced. To evaluate the effectiveness of these machine learning algorithms, this study had chosen four k-fold procedures. Protocols 5, 10, 15, and 20 were the four that were taken. Following these procedures, all eight models assessed the evaluation values shown in Table 6. The K-folds had very little effect on the models' performance.

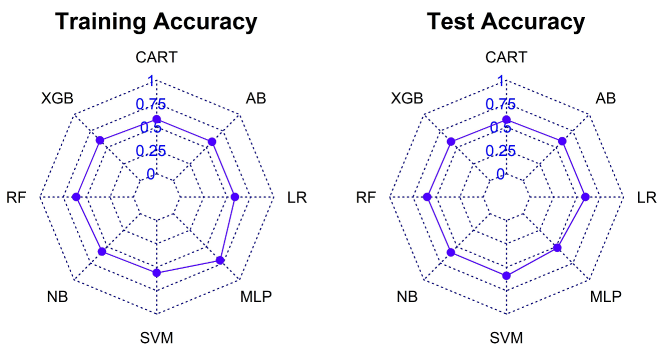

Figure 4. *Schematic plot of the accuracy of machine learning models to predict malnutrition of women using both training and test data sets.*

CART showed that all the folds had around 58% of all metrics for the training data set, whereas test data sets showed little changes in them. For 5 fold, test data sets had 56% of accuracy and the other folds had around 55% of accuracy. Moreover, XGBoost had the same accuracy as the fitted model for the 5 fold of training data set. All other folds including all folds of the test data set had a decrease in evaluation matrices for XGBoost. On the other side, RF showed the same accuracy, precision, recall, and F_1 score of 0.90 for the training data set but had a decrease in the test data set compared to the fitted model. NB had the same matrices of 58% for the training data and 57% for the test data. SVM had gained 57% of accuracy for all the folds of all types of data set. MLP had about 70 percent accuracy for the training data set of all folds but had around half of accuracy for the test data. Furthermore, LR and AB showed almost the same evaluative scores for all folds of training and test data sets which were around 59% and 56%, respectively.

4. Discussion

Maintaining a healthy lifestyle requires eating a balanced diet. This study involves a thorough investigation into the use of machine learning classifiers to identify and predict malnourished women. Eight machine learning algorithms were utilized in both the training and test data sets. Four protocols were also used to evaluate the algorithms. Section 3 presents the results of these machine learning classifiers. Figure 4 displayed the spider plot of the accuracies of the models. It was visible that MLP has the highest accuracy in predicting the malnutrition of women through the training data sets. Moreover, the test data accuracy of RF was the highest among the models. Figure 5 represented the bar plot of accuracy and F_1 score which also showed that both scores were highest for the MLP in the training data but RF outperformed others in terms of predicting malnutrition for the test data sets. To determine the best predictive model, the rank of the models based on their performance had been measured which was also used in a previous study [56].

Each unique model performance has been assigned a rank. The rank had been measured using accuracy, kappa, and F_1 score (Table 7). The CART model was ranked last and had the lowest accuracy along with other matrices based on the prediction of the training data set. The bagging approach had been ranked first for all three evaluative techniques. The neural network technique had the highest accuracy for the training data. However, the models were ranked differently in terms of test accuracy. Regarding predicting female malnutrition, AB had the second-highest accuracy, kappa, and F_1 score (Table 7). RF performed very well to predict using test data and it ranked first for all the metrics. According to the sum of the ranks, RF had the lowest total rank and AB stood second. NB and SVM shared the same overall rank. MLP had highest scores in all metrics but stood 5th in overall. Each of the models that were employed yielded different results and fit the data on women's malnutrition well. Since RF produced findings based on a collection of trees, it fared better than other ML models in predicting malnutrition for training data.

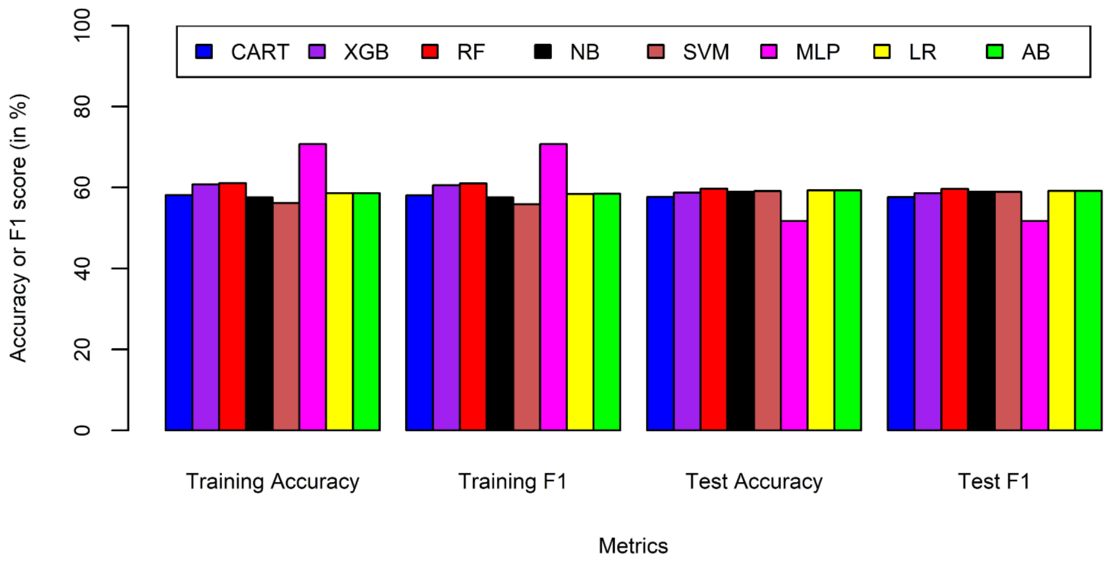

Figure 5. *Plot of the accuracy and F_1 score of machine learning models to predict malnutrition of women using both training and test data sets.*

Table 7. *Rank of different models based on their accuracy, Cohen's Kappa, and F_1 score with rank value for training and test data to forecast malnutrition of Bangladesh evidence from BDSH-2022.*

Model	Training			Test			Rank Sum (Rank)
	Accuracy	Kappa	F_1	Accuracy	Kappa	F_1	
CART	0.58146 (6)	0.16054 (6)	0.58082 (6)	0.57680 (6)	0.15200 (7)	0.57641 (7)	40 (7)
XGB	0.60781 (3)	0.21166 (3)	0.60568 (3)	0.58746 (5)	0.17215 (6)	0.58609 (6)	26 (4)
RF	0.61095 (2)	0.21936 (2)	0.61013 (2)	0.59749 (1)	0.19286 (1)	0.59669 (1)	09 (1)
NB	0.57598 (7)	0.15070 (7)	0.57589 (7)	0.58934 (4)	0.17736 (5)	0.58909 (5)	35 (6)
SVM	0.56155 (8)	0.11837 (8)	0.55881 (8)	0.59122 (3)	0.17929 (4)	0.58940 (4)	35 (6)
MLP	0.70739 (1)	0.41352 (1)	0.70717 (1)	0.51724 (8)	0.03337 (8)	0.51714 (8)	27 (5)
LR	0.58601 (5)	0.16840 (5)	0.58435 (5)	0.59310 (2)	0.18333 (3)	0.59159 (3)	23 (3)
AB	0.58617 (4)	0.16875 (4)	0.58455 (4)	0.59310 (2)	0.18339 (2)	0.59166 (2)	18 (2)

Therefore, based on all of the findings, this study concluded that RF was the most effective predictive machine learning classifier for predicting women's malnutrition.

5. Conclusion

Malnutrition is a dangerous illness brought on by the body not getting enough energy and minerals. It is a major public health issue in all developing countries. In Bangladesh as well, it remains a significant problem, especially for women. Both undernutrition and overnutrition are regarded as forms of malnutrition and are associated with several infectious diseases. Moreover, it has detrimental effects on children, including early birth, weakened immunity to infections, and heightened mortality risk. To protect women from diseases that are exacerbated by malnutrition, it is imperative to identify its causes early. This study involved a thorough investigation into the use of machine learning classifiers for the identification and prediction of malnourished women. Approximately 7972 women were chosen to carry out the research. A total of nineteen variables were chosen for this study's purpose of determining women's nutritional status and fifteen had a substantial correlation with the exposure variable. ML-based algorithms for predicting Bangladeshi women's malnutrition also employed these important aspects as explanatory variables. To determine whether a female was malnourished based on risk factors, this study examined eight machine learning algorithms: Naive Bayes, Classification and Regression Tree, Support Vector Machine, Logistic Regression, AdaBoost, Multilayer Perceptron, Random Forest, and Extreme Gradient Boosting Machine. According to the investigation's findings, Random Forest was the best classifier overall for the test data sets in terms of accuracy, Kappa, and F_1 score. However, when it came to the training data set, MLP became the most accurate model for prediction. Also from the k-fold validation, the same scenario had been revealed. According to this study, all decision tree-based classifiers performed exceptionally well in assessing women's malnutrition, although Random Forest was the most effectively used. Multilayer Perceptron would be the best predictive method for predicting using the training data set but because

Random Forest performed better than the other models overall included in the study, this technique should be used as the best prediction-based approach for predicting malnutrition in Bangladeshi women. To reduce major issues and the strain on the healthcare system, this research will help regulators and healthcare professionals create a framework for implementing the required interventions and care practices. Apart from the consequences for community health, the study demonstrated how the ML technique may be used to more precisely forecast the root causes of women's malnutrition. This study may lead to a better knowledge of women's nutritional status and the creation of more successful programs to improve women's nutrition across the country. Initiatives and programs that target women of all ages and places require an improvement in the socioeconomic status of women in Bangladesh. Therefore, a model that considers the fundamental forms of risk would help prevent and manage female malnutrition. The ethical ramifications of applying machine learning algorithms in healthcare, especially in low- or middle-income nations with weak regulatory frameworks, include issues with patient privacy, informed consent, bias reduction, and the necessity of laws and regulations to guarantee the responsible and equitable use of AI in healthcare. To successfully and ethically implement machine learning into healthcare systems, a few ethical considerations must be addressed. This study employed cross-sectional BDHS data and was exclusively concerned with women. As a result, the ML models may not work as well for the other demographic groupings. It was challenging to apply various feature selection strategies effectively within the constraints of this study due to the dataset's size and properties. As a result, the current work focused on a specific set of machine learning models and feature selection methods. To overcome these constraints and improve the depth and durability of the analysis, future work will use longitudinal data sets, increase processing power, and improve dataset preprocessing to encompass a greater range of models and feature selection strategies.

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Author Contributions

Md. Habibur Rahman: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Resources, Software, Supervision, Validation, Visualization, Writing - original draft, Writing - review & editing

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Not applicable.

Availability of Data and Materials

The data utilized in this study originates from the DHS Program database, accessible at https://dhsprogram.com/Data/. While the datasets employed are available from the corresponding author upon request, further inquiries should be directed to them.

Conflicts of Interest

The author states that they do not have any conflicts of interest.

References

[1] Black, R. E., Victora, C. G., Walker, S. P., Bhutta, Z. A., Christian, P., De Onis, M., Ezzati, M., Grantham-McGregor, S., Katz, J., Martorell, R. and Uauy, R., 2013. Maternal and child undernutrition and overweight in low-income and middle-income countries. The Lancet, 382(9890), pp. 427-451. https://doi.org/10.1016/S0140-6736(13)60937-X

[2] Kapoor, S. K. and Anand, K., 2002. Nutritional transition: a public health challenge in developing countries. Journal of Epidemiology & Community Health, 56(11), pp. 804-805.

[3] Tanwi, T. S., Chakrabarty, S. and Hasanuzzaman, S., 2019. Double burden of malnutrition among ever-married women in Bangladesh: a pooled analysis. BMC women's health, 19, pp. 1-8. https://doi.org/10.1186/s12905-019-0725-2

[4] WHO, 2024. Malnutrition. https://shorturl.at/ppC4q. September, 2024.

[5] Phelps, N. H., Singleton, R. K., Zhou, B., Heap, R. A., Mishra, A., Bennett, J. E., Paciorek, C. J., Lhoste, V. P., Carrillo-Larco, R. M., Stevens, G. A. and Rodriguez-Martinez, A., 2024. Worldwide trends in underweight and obesity from 1990 to 2022: a pooled analysis of 3663 population-representative studies with 222 million children, adolescents, and adults. The Lancet, 403(10431), pp. 1027-1050. https://doi.org/10.1016/S0140-6736(23)02750-2

[6] Islam, M. M., Rahman, M J., Islam, M. M., Roy, D. C., Ahmed, N. F., Hussain, S., Amanullah, M., Abedin, M. M. and Maniruzzaman, M., 2022. Application of machine learning based algorithm for prediction of malnutrition among women in Bangladesh. International Journal of Cognitive Computing in Engineering, 3, pp. 46-57. https://doi.org/10.1016/j.ijcce.2022.02.002

[7] Kc, B., 2019. Factors responsible for non-communicable diseases among Bangladeshi adults. Biomedical Journal of Scientific & Technical Research, 20(1), pp. 14742-14748. https://doi.org/10.26717/BJSTR.2019.20.003388

[8] Nyberg, S. T., Batty, G. D., Pentti, J., Virtanen, M., Alfredsson, L., Fransson, E. I., Goldberg, M., Heikkilä, K., Jokela, M., Knutsson, A. and Koskenvuo, M., 2018. Obesity and loss of disease-free years owing to major non-communicable diseases: a multicohort study. The lancet Public health, 3(10), pp. e490-e497. https://doi.org/10.1016/S2468-2667(18)30139-7

[9] Rahman, A. and Sathi, N. J., 2021. Sociodemographic risk factors of being underweight among ever-married Bangladeshi women of reproductive age: a multilevel analysis. Asia Pacific Journal of Public Health, 33(2-3), pp. 220-226. https://doi.org/10.1177/101053952097992

[10] Rawal, L. B., Kanda, K., Mahumud, R. A., Joshi, D., Mehata, S., Shrestha, N., Poudel, P., Karki, S. and Renzaho, A., 2018. Prevalence of underweight, overweight and obesity and their associated risk factors in Nepalese adults: Data from a Nationwide Survey, 2016. PloS one, 13(11), p. e0205912. https://doi.org/10.1371/journal.pone.0205912

[11] Boutari, C., Pappas, P. D., Mintziori, G., Nigdelis, M. P., Athanasiadis, L., Goulis, D. G. and Mantzoros, C. S., 2020. The effect of underweight on female and male reproduction. Metabolism, 107, p. 154229. https://doi.org/10.1016/j.metabol.2020.154229

[12] Khan, M. N., Rahman, M. M., Shariff, A. A., Rahman, M. M., Rahman, M. S. and Rahman, M. A., 2017. Maternal undernutrition and excessive body weight and risk of birth and health outcomes. Archives of Public Health, 75, pp. 1-10. https://doi.org/10.1186/s13690-017-0181-0

[13] Melchor, I., Burgos, J., Del Campo, A., Aiartzaguena, A., Gutiérrez, J. and Melchor, J. C., 2019. Effect of maternal obesity on pregnancy outcomes in women delivering singleton babies: a historical cohort study. Journal of perinatal medicine, 47(6), pp. 625-630. https://doi.org/10.1515/jpm-2019-0103

[14] Ismail, S. R., Mehmood, A., Rabiah, N., Abu-sulaiman, R. M. and Kabbani, M. S., 2021. Impact of the nutritional status of children with congenital heart diseases on the early post-operative outcome. Egyptian Pediatric Association Gazette, 69, pp. 1-8. https://doi.org/10.1186/s43054-021-00077-9

[15] Pal, A., Manna, S., Dalui, R., Mukhopadhyay, R. and Dhara, P. C., 2021. Undernutrition and associated factors among children aged 5-10 years in West Bengal, India: a community-based cross-sectional study. Egyptian Pediatric Association Gazette, 69, pp. 1-12. https://doi.org/10.1186/s43054-021-00087-7

[16] Ahmad, D., Afzal, M. and Imtiaz, A., 2020. Effect of socioeconomic factors on malnutrition among children in Pakistan. Future Business Journal, 6, pp. 1-11. https://doi.org/10.1186/s43093-020-00032-x

[17] Ekholuenetale, M., Tudeme, G., Onikan, A. and Ekholuenetale, C. E., 2020. Socioeconomic inequalities in hidden hunger, undernutrition, and overweight among under-five children in 35 sub-Saharan Africa countries. Journal of the Egyptian Public Health Association, 95, pp. 1-15. https://doi.org/10.1186/s42506-019-0034-5

[18] Hagos, S., Hailemariam, D., WoldeHanna, T. and Lindtjørn, B., 2017. Spatial heterogeneity and risk factors for stunting among children under age five in Ethiopia: A Bayesian geo-statistical model. PLoS One, 12(2), p. e0170785. https://doi.org/10.1371/journal.pone.0170785

[19] Thompson, D.S., Younger-Coleman, N., Lyew-Ayee, P., Greene, L. G., Boyne, M. S. and Forrester, T. E., 2017. Socioeconomic factors associated with severe acute malnutrition in Jamaica. PloS one, 12(3), p. e0173101. https://doi.org/10.1371/journal.pone.0173101

[20] Ekholuenetale, M., Barrow, A., Ekholuenetale, C. E. and Tudeme, G., 2020. Impact of stunting on early childhood cognitive development in Benin: evidence from Demographic and Health Survey. Egyptian Pediatric Association Gazette, 68, pp. 1-11. https://doi.org/10.1186/s43054-020-00043-x

[21] Rahman, M. S., Mushfiquee, M., Masud, M. S. and Howlader, T., 2019. Association between malnutrition and anemia in under-five children and women of reproductive age: Evidence from Bangladesh Demographic and Health Survey 2011. PloS one, 14(7), p. e0219170. https://doi.org/10.1371/journal.pone.0219170

[22] Abedin, M. M., Haque, M. E., Sabiruzzaman, M., Al Mamun, A. S. M. and Hossain, M. G., 2019. Multinomial logistic regression analysis of factors influencing malnutrition of non-pregnant married women in Bangladesh: Evidence from Bangladesh Demographic and Health Survey-2014. 7th International Conference on Data Science and SDGs: Challenges, Opportunities and Realities, (18-19 December, 2019), Department of Statistics, University of Rajshahi, Bangladesh.

[23] Hossain, M. M., Islam, M. R., Sarkar, A. S. R., Khan, M. M. A. and Taneepanichskul, S., 2018. Prevalence and determinants risk factors of underweight and overweight among women in Bangladesh. Obesity Medicine, 11, pp. 1-5. https://doi.org/10.1016/j.obmed.2018.05.002

[24] Khanam, R, Lee, ASCC, Ram, M, Quaiyum, M, Begum, N, Choudhury, A, Christian, P, Mullany, LC & Baqui, AH 2018. 'Levels and correlates of nutritional status of women of childbearing age in rural Bangladesh', Public health nutrition, vol. 21, no. 16, pp. 3037-3047. https://doi.org/10.1017/S1368980018001970

[25] Kumar, D., Goel, N. K., Mittal, P. C. and Misra, P., 2006. Influence of infant-feeding practices on nutritional status of under-five children. The Indian Journal of Pediatrics, 73, pp. 417-421. https://doi.org/10.1007/BF02758565

[26] Frongillo Jr, E. A., de Onis, M. and Hanson, K. M., 1997. Socioeconomic and demographic factors are associated with worldwide patterns of stunting and wasting of children. The Journal of Nutrition, 127(12), pp. 2302-2309. https://doi.org/10.1093/jn/127.12.2302

[27] Ngiam, K. Y. and Khor, W., 2019. Big data and machine learning algorithms for health-care delivery. The Lancet Oncology, 20(5), pp. e262-e273. https://doi.org/10.1016/S1470-2045(19)30149-4

[28] Alghamdi, M., Al-Mallah, M., Keteyian, S., Brawner, C., Ehrman, J. and Sakr, S., 2017. Predicting diabetes mellitus using SMOTE and ensemble machine learning approach: The Henry Ford ExercIse Testing (FIT) project. PloS one, 12(7), p. e0179805. https://doi.org/10.1371/journal.pone.0179805

[29] Jaiswal, M., Srivastava, A. and Siddiqui, T. J., 2019. Machine learning algorithms for anemia disease prediction. In Recent trends in communication, computing, and electronics: Select proceedings of IC3E 2018 (pp. 463-469). Springer Singapore.

[30] Khan, J. R., Chowdhury, S., Islam, H. and Raheem, E., 2019. Machine learning algorithms to predict the childhood anemia in Bangladesh. Journal of Data Science, 17(1), pp. 195-218. https://doi.org/10.6339/JDS.201901_17(1).0009

[31] Appiahene, P., Asare, J. W., Donkoh, E. T., Dimauro, G. and Maglietta, R., 2023. Detection of iron deficiency anemia by medical images: a comparative study of machine learning algorithms. BioData Mining 16(2). https://doi.org/10.1186/s13040-023-00319-z

[32] Hsieh, C. H., Lu, R. H., Lee, N. H., Chiu, W. T., Hsu, M. H. and Li, Y. C. J., 2011. Novel solutions for an old disease: diagnosis of acute appendicitis with random forest, support vector machines, and artificial neural networks. Surgery, 149(1), pp. 87-93. https://doi.org/10.1016/j.surg.2010.03.023

[33] Louridi, N., Douzi, S. and El Ouahidi, B., 2021. Machine learning-based identification of patients with a cardiovascular defect. Journal of Big Data, 8(1), p. 133. https://doi.org/10.1186/s40537-021-00524-9

[34] Laatifi, M., Douzi, S., Bouklouz, A., Ezzine, H., Jaafari, J., Zaid, Y., El Ouahidi, B. and Naciri, M., 2022. Machine learning approaches in Covid-19 severity risk prediction in Morocco. Journal of Big Data, 9(1), p. 5. https://doi.org/10.1186/s40537-021-00557-0

[35] Rezaeijo, S. M., Ghorvei, M., Abedi-Firouzjah, R. et al., 2021. Detecting COVID-19 in chest images based on deep transfer learning and machine learning algorithms. Egypt J Radiol Nucl Med 52(145). https://doi.org/10.1186/s43055-021-00524-y

[36] Meng, X. H., Huang, Y. X., Rao, D. P., Zhang, Q. and Liu, Q., 2013. Comparison of three data mining models for predicting diabetes or prediabetes by risk factors. The Kaohsiung Journal of Medical Sciences, 29(2), pp. 93-99. https://doi.org/10.1016/j.kjms.2012.08.016

[37] Nibareke, T. and Laassiri, J., 2020. Using Big Data-machine learning models for diabetes prediction and flight delays analytics. Journal of Big Data, 7(1), p. 78. https://doi.org/10.1186/s40537-020-00355-0

[38] Sharma, T. and Shah, M., 2021. A comprehensive review of machine learning techniques on diabetes detection. Visual Computing for Industry, Biomedicine, and Art, 4, p. 30. https://doi.org/10.1186/s42492-021-00097-7

[39] Yu, W., Liu, T., Valdez, R., Gwinn, M. and Khoury, M. J., 2010. Application of support vector machine modeling for prediction of common diseases: the case of diabetes and pre-diabetes. BMC Medical Informatics and Decision Making, 10, pp. 1-7. https://doi.org/10.1186/1472-6947-10-16

[40] Islam, M. M., Rahman, M. J., Roy, D. C., Tawabunnahar, M., Jahan, R., Ahmed, N. F. and Maniruzzaman, M., 2021. Machine learning algorithm for characterizing risks of hypertension, at an early stage in Bangladesh. Diabetes & Metabolic Syndrome: Clinical Research & Reviews, 15(3), pp. 877-884. https://doi.org/10.1016/j.dsx.2021.03.035

[41] Zhao, H., Zhang, X., Xu, Y., Gao, L., Ma, Z., Sun, Y. and Wang, W., 2021. Predicting the risk of hypertension based on several easy-to-collect risk factors: a machine learning method. Frontiers in Public Health, 9, p. 619429. https://doi.org/10.3389/fpubh.2021.619429

[42] Islam Pollob, S. A., Abedin, M. M., Islam, M. T., Islam, M. M. and Maniruzzaman, M., 2022. Predicting risks of low birth weight in Bangladesh with machine learning. PLOS One, 17(5), p. e0267190. https://doi.org/10.1371/journal.pone.0267190

[43] Borson, N. S., Kabir, M. R., Zamal, Z. and Rahman, R. M., 2020, July. Correlation analysis of demographic factors on low birth weight and prediction modeling using machine learning techniques. In 2020 Fourth World Conference on Smart Trends in Systems, Security and Sustainability (WorldS4) (pp. 169-173). IEEE. https://doi.org/10.1109/WorldS450073.2020.9210338

[44] Eliyati, N., Faruk, A., Kresnawati, E. S., & Arifieni, I. (2019). Support vector machines for classification of low birth weight in Indonesia. Journal of Physics: Conference Series, 1282. https://api.semanticscholar.org/CorpusID:202144807

[45] Faruk, A., Cahyono, E. S., Eliyati, N. and Arifieni, I., 2018. Prediction and classification of low birth weight data using machine learning techniques. Indonesian Journal of Science and Technology, 3(1), pp. 18-28. https://doi.org/10.17509/ijost.v3i1.10799

[46] Bekele, W. T., 2022. Machine learning algorithms for predicting low birth weight in Ethiopia. BMC Medical Informatics and decision making, 22(1), p. 232. https://doi.org/10.1186/s12911-022-01981-9

[47] Talukder, A. and Ahammed, B., 2020. Machine learning algorithms for predicting malnutrition among under-five children in Bangladesh. Nutrition, 78, p. 110861. https://doi.org/10.1016/j.nut.2020.110861

[48] Shahriar, M. M., Iqubal, M. S., Mitra, S. and Das, A. K., 2019, July. A Deep Learning Approach to Predict Malnutrition Status of 0-59 Month's Older Children in Bangladesh. In 2019 IEEE International Conference on Industry 4.0, Artificial Intelligence, and Communications Technology (IAICT) (pp. 145-149). IEEE. https://api.semanticscholar.org/CorpusID:199488688

[49] Khare, S., Kavyashree, S., Gupta, D. and Jyotishi, A., 2017. Investigation of nutritional status of children based on machine learning techniques using Indian demographic and health survey data. Procedia computer science, 115, pp. 338-349. https://doi.org/10.1016/j.procs.2017.09.087

[50] Bitew, F. H., Nyarko, S. H., Potter, L. and Sparks, C. S., 2020. Machine learning approach for predicting under-five mortality determinants in Ethiopia: evidence from the 2016 Ethiopian Demographic and Health Survey. Genus, 76, pp. 1-16. https://doi.org/10.1186/s41118-020-00106-2

[51] Reis, R., Peixoto, H., Machado, J. and Abelha, A., 2017. Machine learning in nutritional follow-up research. Open Computer Science, 7(1), pp. 41-45.

[52] Momand, Z., Mongkolnam, P., Kositpanthavong, P. and Chan, J. H., 2020, January. Data mining based prediction of malnutrition in Afghan children. In 2020 12th International Conference on Knowledge and Smart Technology (KST) (pp. 12-17). IEEE.

[53] Rahman, S. M. J., Ahmed, N. A. M. F., Abedin, M. M., Ahammed, B., Ali, M., Rahman, M. J., Maniruzzaman, M., 2021. Investigate the risk factors of stunting, wasting, and underweight among under-five Bangladeshi children and its prediction based on machine learning approach. PLoS ONE 16(6), p. e0253172. https://doi.org/10.1371/journal.pone.0253172

[54] Markos, Z., Doyore, F., Yifiru, M. and Haidar, J., 2014. Predicting Under nutrition status of under-five children using data mining techniques: The Case of 2011 Ethiopian Demographic and Health Survey. J Health Med Inform, 5(2), p. 152. https://doi.org/10.4172/2157-7420.1000152

[55] Khudri, M. M., Rhee, K. K., Hasan, M. S. and Ahsan, K. Z., 2023. Predicting nutritional status for women of childbearing age from their economic, health, and demographic features: A supervised machine learning approach. Plos one, 18(5), p. e0277738. https://doi.org/10.1371/journal.pone.0277738

[56] Turjo, E. A. and Rahman, M. H., 2024. Assessing risk factors for malnutrition among women in Bangladesh and forecasting malnutrition using machine learning approaches. BMC Nutrition, 10(1), p. 22. https://doi.org/10.1186/s40795-023-00808-8

[57] NIPORT: Bangladesh Demographic and Health Survey 2022, 2024, https://niport.portal.gov.bd. Dhaka, Bangladesh: NIPORT/ICF

[58] WHO, O., 2000, Preventing and managing the global epidemic. geneva. WHO Technical report series 894, 252.

[59] Ahmed, K. Y., Rwabilimbo, A. G., Abrha, S., Page, A., Arora, A., Tadese, F., Beyene, T. Y., Seiko, A., Endris, A. A., Agho, K. E. and Ogbo, F. A., 2020. Factors associated with underweight, overweight, and obesity in reproductive age Tanzanian women. PloS one, 15(8), p. e0237720. https://doi.org/10.1371/journal.pone.0237720

[60] Han, J., Kamber, M., Pei, J., 2012, Data mining concepts and techniques third edition. 34 University of Illinois at Urbana-Champaign Micheline Kamber Jian Pei Simon Fraser University.

[61] Cover, T. M., 1965. Geometrical and statistical properties of systems of linear inequalities with applications in pattern recognition. IEEE Transactions on electronic computers, (3), pp. 326-334. https://doi.org/10.1109/PGEC.1965.264137

[62] Breiman, L., 2017. Classification and regression trees. Routledge.

[63] Gutierrez, D. D., 2015. Machine learning and data science: an introduction to statistical learning methods with R. Technics Publications.

[64] Breiman, L., 2001. Random forests. Machine learning, 45, pp. 5-32.

[65] Hastie, T., Tibshirani, R., Friedman, J. H., Friedman, J. H., 2017, The Elements of Statistical Learning: Data Mining, Inference, and Prediction, 2nd ed. Springer, California, USA.

[66] Freund, Y., Schapire, R. E., 1995. A desicion-theoretic generalization of on-line learning and an application to boosting. In: Vitányi, P. (eds) Computational Learning Theory. EuroCOLT 1995. Lecture Notes in Computer Science, vol 904. Springer, Berlin, Heidelberg. https://doi.org/10.1007/3-540-59119-2_166

[67] Chen, T. and Guestrin, C., 2016, August. Xgboost: A scalable tree-boosting system. In Proceedings of the 22nd acm sigkdd International Conference on knowledge discovery and Data Mining (pp. 785-794). https://doi.org/10.1145/2939672.2939785

[68] Cybenko, G., 1989. Approximations by superpositions of a sigmoidal function. Mathematics of Control, Signals and Systems, 2, pp. 183-192. https://doi.org/10.1007/BF02551274

[69] Amari, S., 1967. A theory of adaptive pattern classifiers. IEEE Transactions on Electronic Computers, (3), pp. 299-307. https://doi.org/10.1109/PGEC.1967.264666

[70] Haykin, S., 2009. Neural networks and learning machines, 3/E. Pearson Education India.

[71] Cifuentes, J., Marulanda, G., Bello, A. and Reneses, J., 2020. Air temperature forecasting using machine learning techniques: a review. Energies, 13(16), p. 4215. https://doi.org/10.3390/en13164215

[72] Paul, S. and Roy, S., 2020. Forecasting the average temperature rise in Bangladesh: a time series analysis. Journal of Engineering Science, 11(1), pp. 83-91. https://doi.org/10.3329/jes.v11i1.49549

[73] Cortes, C., Vapnik, V., 1995. Support-vector networks. Mach Learn 20, p. 273-297. https://doi.org/10.1007/BF00994018

[74] Brownlee, J., 2016. Machine learning mastery with R: Get started, build accurate models and work through projects step-by-step. Machine Learning Mastery.

[75] Landis, J. R. and Koch, G. G., 1977. The measurement of observer agreement for categorical data. Biometrics, pp. 159-174. https://doi.org/10.2307/2529310