International Journal for Multidisciplinary Research (IJFMR)
E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

Leveraging Machine Learning Techniques to Effectively Predict Malnutrition Among Children

Reshma Tushar Ladda[1], Prof. Dr. Babasaheb Sonawane[2]

[1,2]Dept. of Computer Science& Engineering, Marathwada Institute of Technology (MIT), Satara Rd, Chhatrapati Sambhajinagar.

Abstract:
The objective of the research is to predict malnutrition in children through the application of different algorithms in machine learning. The lack of adequate muscle and fat tissue development during intrauterine growth is a hallmark of malnutrition. It is mostly brought on by inadequate nourishment for the mother and placental insufficiency, which results in lower rates of infant morbidity and mortality across the world. This study focuses on to determine whether malnutrition is present in children by calculating their Z-score, which takes into consideration age in months, weight, peak, and sex. The dataset that was used in this project was obtained for network education from UNICEF. The given dataset is divided into two parts: one for verification and the other for analysis. We identify infant malnutrition by calculating WAZ (underweight) and LAZ (stunting), and we train the fashions to do so. Several machine learning techniques, such as logistic regression, KNN, and Naïve Bayes, are used to identify childhood malnutrition. Out of all these designs, logistic regression shows better accuracy than the other algorithms.

Keywords: Malnutrition, WAZ (Weight for age Z score) or underweight, HAZ (Height for age Z score) or stunting, ML (Machine Learning), KNN, Logistic Regression, Naïve Bayes Algorithm

1. INTRODUCTION

A condition known as malnutrition is defined by imbalances, deficiencies or excesses in an individual's energy and nutrient intake. Malnutrition can be divided into two significant groups. The term "undernutrition," which describes inadequate nutritional intake as the primary cause of stunted growth and underweight conditions, is the first institution. The second organization is linked to eating too much food, which is a major cause of health issues like diabetes, heart disease, and obesity. [1-2].
Children under the age of five are particularly vulnerable to malnutrition, which is responsible for over half of all neonatal fatalities. It not only makes common infections more severe, but it also raises the risk of dying from those illnesses. Malnutrition can be indicated and manifested as weariness, exhaustion, scaly, dry skin in infants, and chronic illnesses in children [3]. Malnutrition affects about 90 million people worldwide [3]. Every state in the union is experiencing an increase in the number of cases of hunger, with 159 million children under five suffering from malnutrition, 50 million experiencing low-weight loss, and 41 million are obese. [4] [5].

Early nutrition is essential for children because it has a significant impact on their long-term health and reduces the risk of noncommunicable diseases (NCDs). Good diet during the early years of life lowers health risks and ensures healthy growth and development. (UNICEF, 2019) [5-6]. Malnutrition affects one in two children in India and accounts for 69% of under-5 mortality. In India, stunting is a frequent problem that causes irreparable physical harm and impairs cognitive development. The long-term implications of stunting include reduced intellectual ability, and an increased risk of persistent disorders linked to vitamins. [7-8]. This study computes Z-scores for weight for age (WAZ) and height for age (HAZ) measures using a UNICEF dataset.
These datasets can be used to train and test machine learning models such as the Naïve Bayes Algorithm, Regression, and KNN (K-Nearest Neighbor) models.

2. LITERATURE REVIEW

2020 study by Ashis Talukder and Benojir Ahammed attempted forecasting under-five-year-old children's malnutrition. Based on the 2014 Bangladeshi survey carried out by the Bangladesh Demographic and Health Survey (BDHS) department, they suggested a machine learning algorithm. They used the linear discriminant analysis (LDA) technique to predict malnutrition. [9].
Data from the Indian Demographic and Health Survey were used in a study on child nutrition by Sangeeta Khare and others. Their findings showed that undernourished kids have a higher chance of acquiring chronic illnesses like poor wound healing, prolonged hospital admissions, a decreased ability to move around, a higher risk of fractures, muscular atrophy, weight loss, and low energy. [10].
Artificial neural network (ANN) techniques were used by Shahriar, Md., Iqubalet al. to assess data from the Bangladesh population and health survey (BDHS) of 2014. [11].They investigated the way in which the prediction model characterizes malnourishment. When it came to identifying stunting, underweight, and wasting, the ANN approach showed excellent accuracy.
Omer & Besar et al. gathered information from 37 hospitals spread across 26 distinct locations in Turkey, where they used the PYMS and STRONG procedures to around 1,513 patients suffering from a range of underlying mental health conditions. They computed scores for body mass index to age, z-height to age, and weight to age. Their research demonstrated how anthropometric scales can help classify and prevent malnutrition when used in conjunction with other screening techniques like PYMS. The needs were assessed using anthropometric measurements. It is important to note that the PYM methodology is less sensitive to anthropometric data but more sensitive in diagnosing malnutrition risk than other approaches. [12].
Using a family survey dataset, Duraisamy, Thangamani D, and Sudha Palanichamy created supervised machine learning algorithms and neural networks for classification and prediction. These techniques make it possible to process vast volumes of data and produce reliable results. [13].
To identify nutritional deficits in youngsters, Cynthia Hayat and Barens Abian created a system that uses picture processing and data analysis. By gathering user data and storing it in a database, this module makes it possible to make informed decisions through thorough analysis. [14].
The SCUT (Sampling and Classification Algorithms to Identify Stages of Child Malnutrition) program, which mixes neural networks and decision trees, was used by Juan Gutiérrez-Cárdenas and Juan Baraybar-Huambo to ascertain the most efficient method for identifying patients who are malnourished. The SCUT model showed remarkable improvement in malnutrition identification with excellent accuracy. Yin and others suggested building a decision tree for determining the severity of malnutrition

by applying the classification and regression tree (CART) technique, which is based on the Global Leadership Initiative on Malnutrition (GLIM). [15].

Momand and others employed Random Forest, J48, and Naive Bayes classifiers to gather malnutrition data from Afghan hospitals. With a maximum accuracy of 97.14 percent, the Random Forest technique produced outstanding results; J48 produced results that were comparable, with a maximum accuracy of 94.51 percent.[16]. Over the years, multiple studies have looked at how hunger and malnutrition affect people of all ages. To comprehend the reasons of malnutrition, issues including mathematical considerations, accessibility, health concerns, home situations, physical factors, and socioeconomic challenges have been taken into account. The body mass index (BMI) has been used in many of these studies to measure malnutrition.

Kishore et al. want to use machine learning to predict infant malnutrition. Neonatal malnutrition is a result of both inadequate placental feeding and poor maternal nutrition. Z-scores are computed by taking into account variables including age, weight, height, and sex using a UNICEF dataset. The dataset is split into testing and validation sections.[17] A range of machine learning models are utilized, such as SVM, KNN, logistic regression, Naïve Bayes, and a neural network with two layers. Malnutrition can be detected with greater accuracy when using logistic regression. The study emphasizes how data-driven methods for early identification and intervention can lower the rates of newborn morbidity and mortality around the world.

3. METHODOLOGY

The system studying version's schooling process using the generated datasets is shown in block diagram depicted in Figure 1. The capabilities are extracted from the datasets, and then machine learning methods are employed to train and validate the statistics to provide the desired result. The three often used indicators of malnutrition are WHZ (emaciation), HAZ (stunting), and WAZ (underweight). These indicators provide information about a child's growth and body composition, enabling the assessment of their nutritional status.

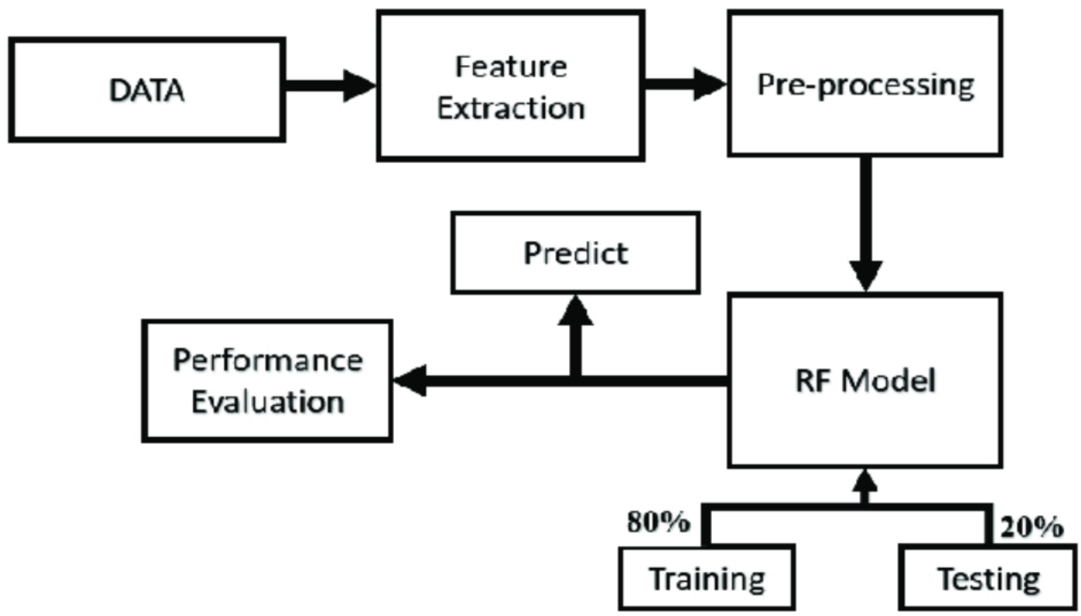

Fig.1. Block Diagram of Machine Learning Model

A Z-score, sometimes referred to as a standard score, is a statistical metric expressed in standard deviations from the mean that illustrates a value's relationship to the mean of a set of values. It displays the number of standard deviations an element deviates from the group mean.
To calculate Z-Score equation (1) is used:

$$\mathrm{Z-Score} = (\mathrm{W}-\mathrm{M})/\mathrm{SD} \qquad \text{------ (1)}$$

W stands for the weight of the individual, M for the median, and SD for the standard deviation.
Likewise, the formula is used in equations (2) and (3) to determine the WAZ and HAZ, respectively.

$$\mathrm{WAZ} = (\mathrm{X}-\mathrm{M})/\mathrm{SD} \qquad \text{------ (2)}$$

$$\mathrm{HAZ} = (\mathrm{Y}-\mathrm{M})/\mathrm{SD} \qquad \text{------ (3)}$$

In this case, WHZ represents the weight for height, WAZ the weight for age, and HAZ the height for age. X and Y represent the age-appropriate weight and height, respectively, while M is the median SD, which represents the standard deviation.
Malnutrition is present if any of the Z-rankings determined by using the aforementioned formulae is significantly less than or equal to -2.0. Next, machine learning algorithms are used to classify the children according to their malnutrition score. To identify childhood malnutrition, Naïve Bayes, logistic regression, and KNN are used. These algorithms' accuracy is seen across all testing and educational levels within the network. UNICEF provides the necessary statistics for the work, and all theoretical calculations are used to generate the Z scores for age-related weight (WAZ) and age-associated top (HAZ). After that, the network is adjusted appropriately for the specific purpose of achieving the goals.

3.1 LOGISTICS REGRESSION

One statistical model i.e. Logistic regression is used for binary category problems—such as determining malnutrition. It is supervised learning algorithm that predict that an example will fit into a particular elegance. When the structured variable is specific and includes two instructions, logistic regression is frequently used. Each elegance is represented by a binary result (malnutrition or non-malnutrition).Logistic regression can be employed in the detection of malnutrition to determine if an infant is malnourished or not, depend on exclusively on positive functions or predictors. These predictors could also include things like height, weight, age, eating habits, and other pertinent factors.
By using the logistic characteristic, also known as the sigmoid feature, the logistic regression version calculates the link between the predictors and the probability of malnutrition. Any real-valued range can be mapped by the sigmoid characteristic to a cost between 0 and 1, which can be seen as the potential for the example to belong to either non-malnourished or the malnourished. The version of logistic regression that estimates each predictor's coefficients indicates how much each predictor influences or contributes to the chances of malnutrition. Usually, the maximum chance estimation method is used to obtain these coefficients.
To reduce the difference between the expected probabilities and the actual elegance labels in the educational facts, the logistic regression version modifies the coefficients during the education phase. This method is typically carried out in combination with gradient descent and optimization methods. Based on function values, the model may be trained to predict if a new instance will experience malnutrition. The expected probabilities can be converted into class labels, whether an instance is malnourished or not, by applying a threshold (e.g., -2.0).Logistic regression assumes a linear relationship between the log-odds of malnutrition and the predictors. Different approaches, such as nonlinear models or polynomial logistic regression, may be taken into consideration if the connection is more complex. All things considered, logistic regression is a helpful set of guidelines for identifying

malnutrition since it provides information about the chances of malnutrition based on a variety of predictors, enabling classification and decision-making in assessing a baby's nutritional condition.
Straight line equation can be written as shown in the equation 4:

$$p = l_0 + l_1 q_1 + l_2 q_2 + l_3 q_3 + \cdots + l_r q_r \qquad \text{------ (4)}$$

Because y in logistic regression can only be between 0 and 1, we divide the following equation by $(1 - p)$: $p/(1 - p)$;0 for p = 0, and infinity for p = 1 ------ (5)
However, if the range is between -[infinity] and +[infinity], the logarithm of the equation becomes:

$$\log [p/(1 - p)] = l\_0 + l\_1\ q\_1 + \cdots + l\_r\ q\_r \qquad \text{------ (6)}$$

3.2 KNN

The K-Nearest Neighbors (KNN) algorithm is a supervised machine learning algorithm used for malnutrition identity. KNN is based totally at the precept that similar times are possible to belong to the equal magnificence.

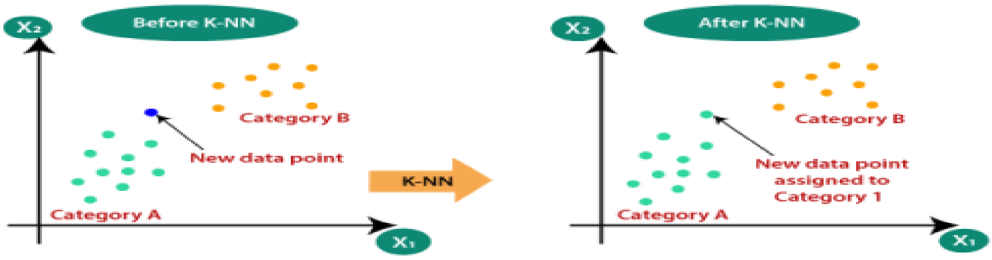

Fig.2.Classification using KNN

The K-Nearest Neighbors (KNN) algorithm for malnutrition identification involves the subsequent steps:

- **Data Preparation:** Gather a categorized dataset that consists of times of kids at the side of their relevant features (e.g. age, weight, height, nutritional conduct, etc.) and corresponding class labels indicating malnourished or not.
- **Feature Scaling:** Normalize or standardize the functions to make sure that every feature contributes equally to the distance calculations. This step is critical because KNN is sensitive to the size of the capabilities.
- Training Phase: KNN is a lazy studying algorithm, because of this that it does no longer explicitly teach a model. Instead, throughout the training segment, KNN simply stores the complete schooling dataset.
- **Distance Calculation:** Calculate the gap between the new instance (child) and all times in the education dataset. The most typically used distance metric is the Euclidean distance, but other distance metrics also can be used depending on the character of the capabilities.
- **Determine K Neighbors**: Select the K nearest acquaintances to the new instance based at the calculated distances. K is a person-defined parameter that determines the range of buddies to recall.
- **Majority Voting:**Among the K buddies, be counted the wide variety of times in each magnificence. The class with the highest remember will become the predicted elegance for the brand-new example.
- **Prediction Phase**: Assign the predicted elegance label to the new instance primarily based on the majority voting result. The desire of K is crucial within the KNN algorithm. A smaller K value may

additionally lead to overfitting, wherein the algorithm is sensitive to outliers or noise inside the information. On the other hand, a bigger K fee may additionally result in underfitting, wherein the algorithm turns into overly influenced by means of the majority magnificence.

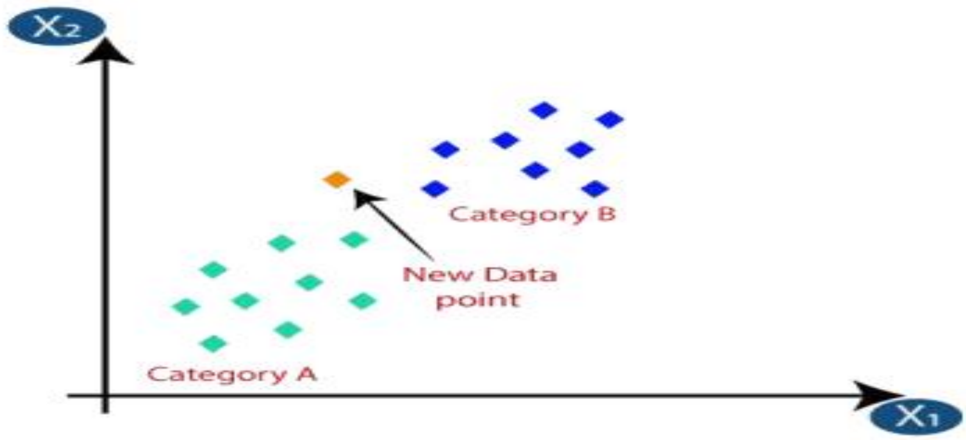

Fig.3. KNN- New Data Points Considered

It is recommended to perform function choice or dimensionality discount strategies before making use of the KNN set of rules to lessen the variety of inappropriate or redundant features and improve the algorithm's performance. KNN is a tremendously simple set of rules, but it can be computationally pricey whilst dealing with massive datasets, as the space calculations need to be done for each new instance. Additionally, KNN does no longer offer insights into the underlying relationships inside the facts because it makes a specialty of instance-primarily based classification. Overall, the KNN set of rules can be an effective method for malnutrition identification, while the dataset is well-organized, and the selection of K is carefully considered.

Illustration of Euclidean Distance calculation:

First, choose k=5 as the number of neighbors. Then Euclidean distance between two neighbors is calculated by using the equation (7).

$$S = \sqrt{(x_2 - x_1)^2 - (y_2 - y_1)^2} \qquad \text{------ (7)}$$

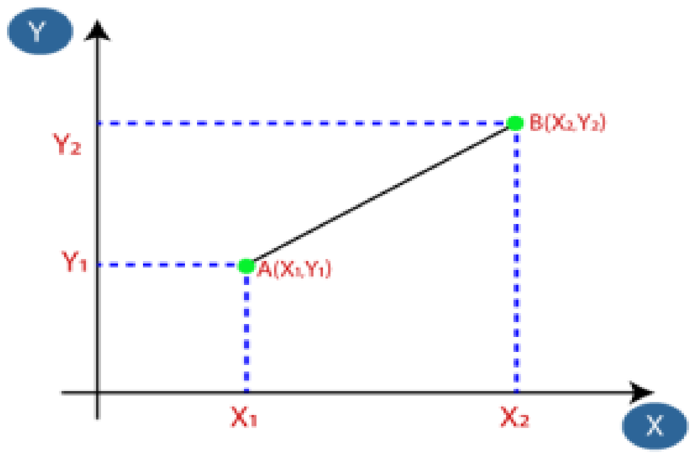

Fig.4.EuclideanDistanceIllustration

In summary, the KNN algorithm determines the class of a new data point based on the classes of its nearest neighbors. By selecting the appropriate number of neighbors (K) and calculating the distances as showing in Figure 2 and Figure 3 and 4, KNN can efficiently classify new data points into the appropriate category.

3.3 Naïve Bayes Algorithm

The Naïve Bayes algorithm is a probabilistic classification algorithm commonly used in machine learning for various tasks, including malnutrition identification. It is based on Bayes' theorem and assumes that all features are independent of each other given the class variable, hence the term "naïve. "Naïve Bayes calculates the probability of an instance belonging to a particular class (e.g., malnourished or non-malnourished) based on the probabilities of its features occurring in each class. The algorithm estimates these probabilities from the training data and uses them to make predictions on new instances.
To apply the Naïve Bayes algorithm for malnutrition identification, we would first need a labelled dataset that includes instances of children with their respective features and class labels indicating whether they are malnourished or not.
The Naïve Bayes algorithm involves the following steps:
Data Preparation: Preprocess the dataset and extract relevant features that may be indicative of malnutrition in children. These features could include age, weight, height, dietary habits, and any other relevant variables.
Training Phase: Calculate the probabilities of each feature occurring in each class (malnourished or non-malnourished) based on the training data. This involves estimating the prior probabilities of each class and the conditional probabilities of each feature given each class.
Prediction Phase: Given a new instance (child), calculate the probability of it belonging to each class using the Bayes' theorem. The class with the highest probability is predicted as the class label for the instance.
The Naïve Bayes algorithm assumes that the features are conditionally independent given the class variable, which may not hold true in all cases. However, it is often a reasonable assumption and has shown to perform well in practice, especially with large datasets. Naïve Bayes is computationally efficient, requires minimal training data, and can handle both numerical and categorical features. However, it may suffer from the "zero-frequency" problem if a feature combination is not present in the training data, and it assumes that all features are equally important, which may not always be the case.
Overall, the Naïve Bayes algorithm can be a useful tool for malnutrition identification, providing a probabilistic framework for classifying children based on their features. It is important to properly preprocess the data and select relevant features to achieve accurate predictions.

$$\mathrm{P(B)} = \mathrm{P(A)P(A)/P(B)} \qquad \text{------ (8)}$$

Where P(A|B) is the Posterior probability: Probability of hypothesis A on the observed event B.
P(B|A) is the Likelihood probability: Probability of the evidence providing the probability of a hypothesis is true.
P(A) is the Prior Probability: Probability of hypothesis before observing the evidence.
P(B) is the Marginal Probability: Probability of Evidence.

4. RESULTS

The effects suggest that out of the algorithms used (KNN, Logistic Regression, Naive Bayes), Logistic

Regression achieved the very best accuracy. Logistic Regression became capable of as it should be classifying malnourished youngsters primarily based at the scatter plot of WAZ and LAZ, with an accuracy of 95.9% for WAZ and 94.8% for LAZ. The scatter plot which become shown in Figure 5, 6 visualizes the facts points, wherein blue dots constitute children categorized as malnourished (Z-score under -2) and crimson dots represent kids labelled as non-malnourished (Z-rating above -2).

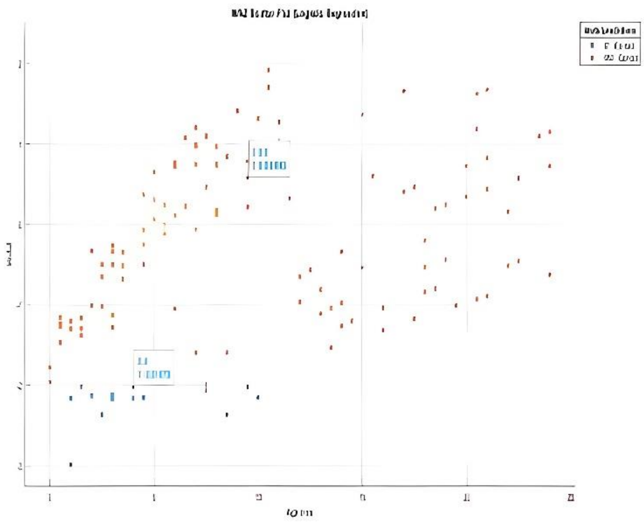

Fig.5. Scatter plots of WAZ using Logistic Regression

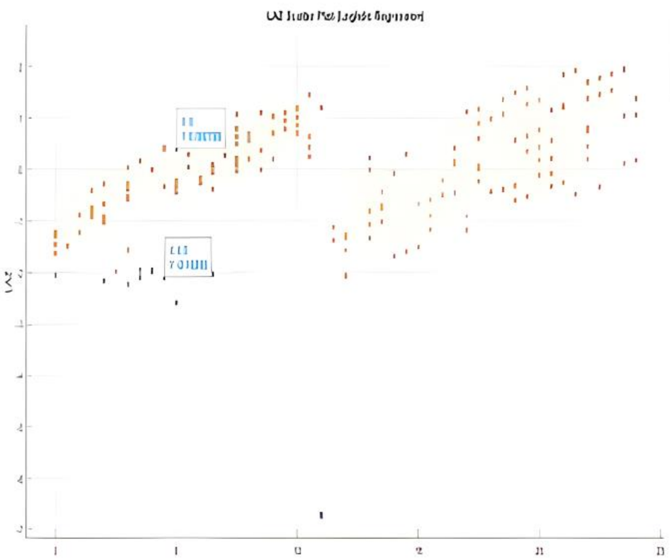

Fig.6. Scatter plots of LAZ using Logistic Regression

LAZ of logistic regression is shown in Figure 7 and 8 show the ROC curve. These results suggest that Logistic Regression is a promising set of rules for the identity of malnutrition in children, accomplishing excessive accuracy in category primarily based on weight-for-age (WAZ) and peak-for-age (LAZ) Z-rankings.

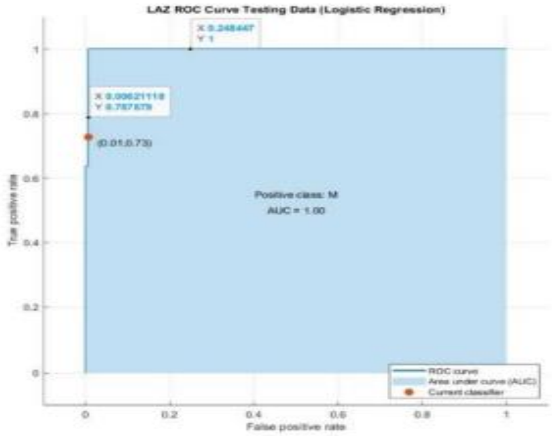

Fig.7. WAZ ROC Curve using Logistic Regression

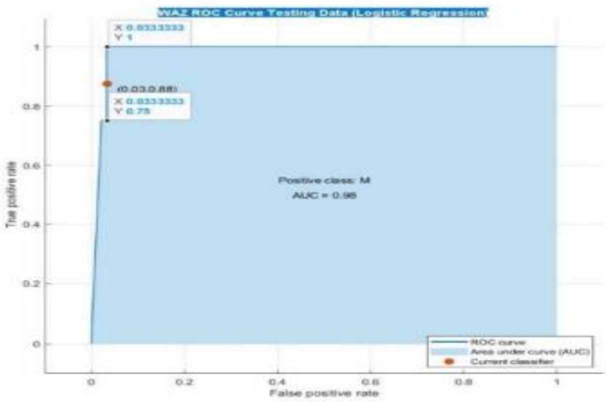

Fig.8. LAZ ROC Curve using Logistic Regression

Figure 9 and 10 below shows the scatter plot of WAZ using KNN and Values below -2.0, Z-score mean that the children are malnourished, indicated by blue dots, and values above -2.0 mean that they are not malnourished, indicated by red dots.

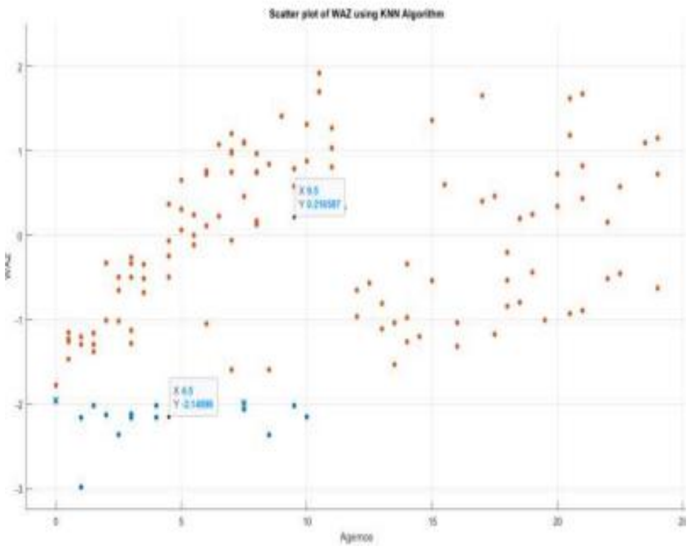

Fig.9.Scatterplot for WAZ using KNN

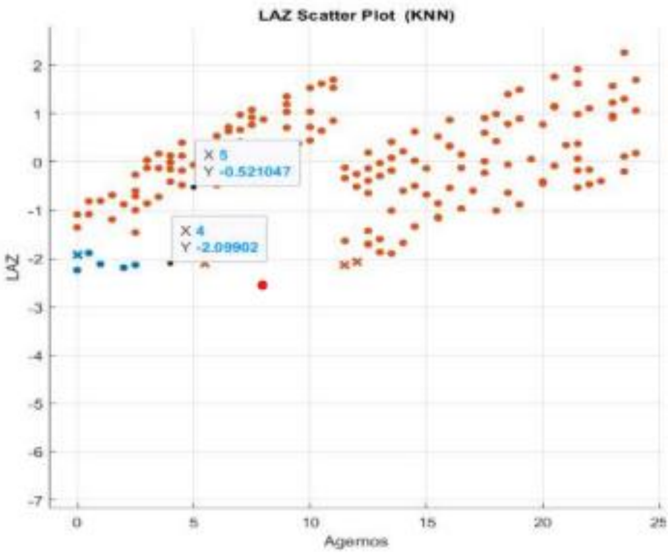

Fig.10. Scatterplot for LAZ using KNN

The KNN algorithm provides an accuracy of 95.9% for WAZ and 94.3 % for LAZ. Figures 11 and 12 show the ROC curve of the KNN, respectively.

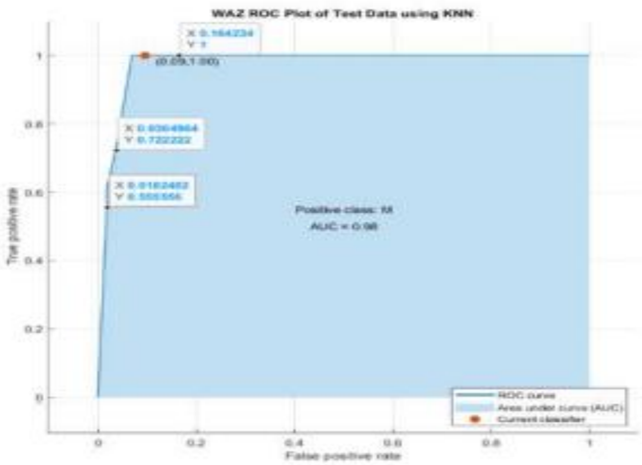

Fig.11.WAZ ROC Curve using KNN

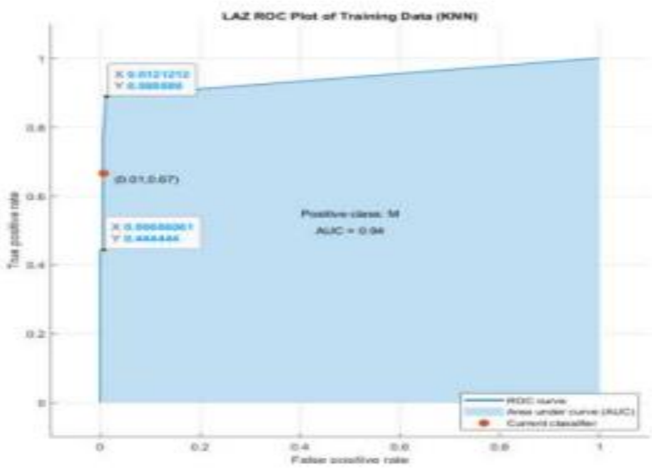

Fig.12. LAZ ROC Curve using KNN

Figure 13 and 14 beneath suggests the scatter plot of LAZ and WAZ the usage of Naive Bayes Algorithm and Values under -2.0 Z-rating imply that the kids are malnourished, indicated through blue dots, and values above -2 mean that they are not malnourished, indicated by way of pink dots.

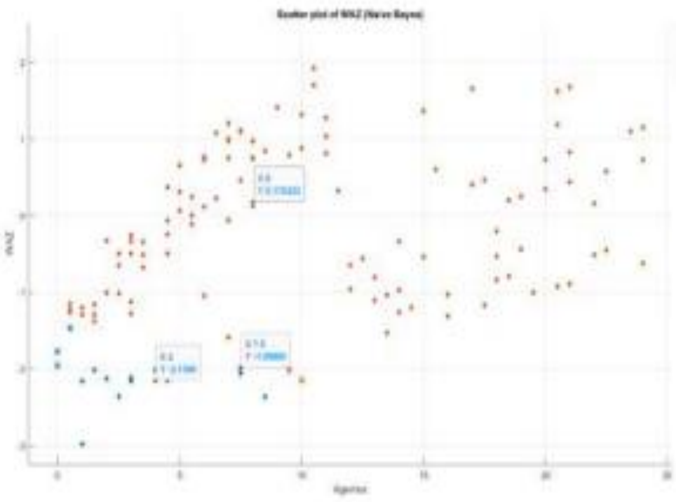

Fig.13. Scatterplot of WAZ for Naive Bayes Algorithm

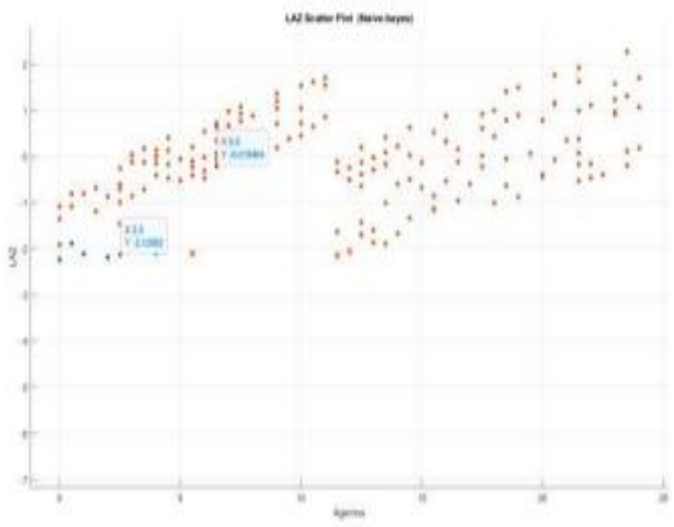

Fig.14. Scatterplot of LAZ for Naive Bayes Algorithm

The Naive Bayes set of rules provides an accuracy of 95.4% for WAZ and 93.8 % for LAZ. Figures 15 and 16 display the ROC curve of the Naive Bayes, respectively.

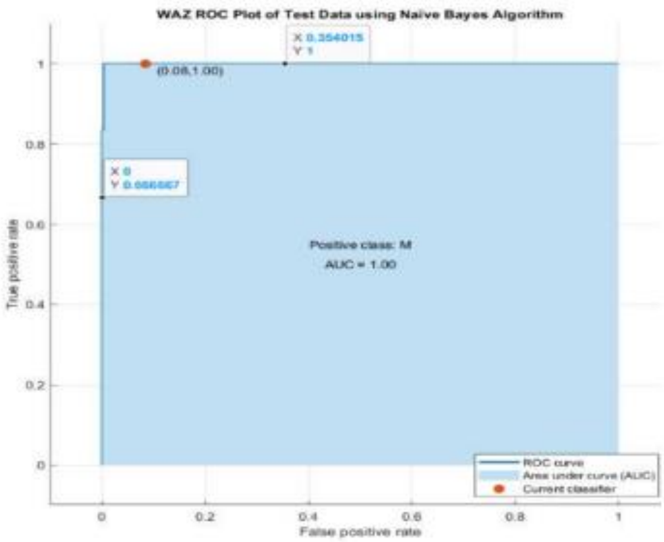

Fig. 15. WAZ ROC Curve for Naive Bayes Algorithm

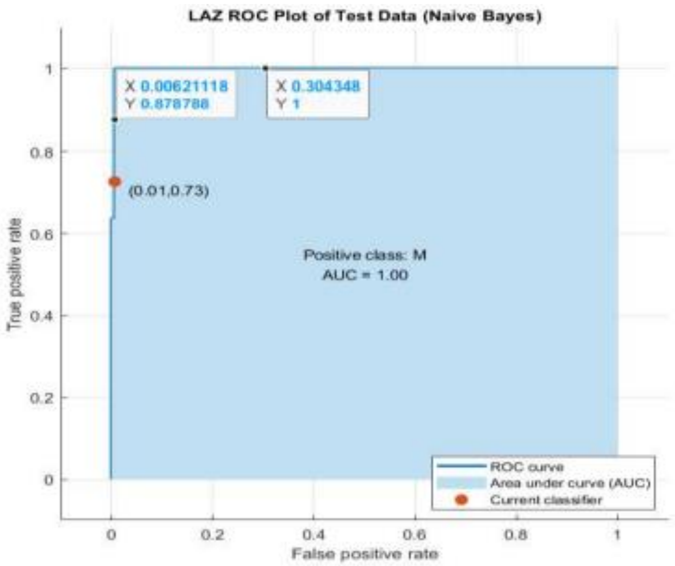

Fig. 16. LAZ ROC Curve for Naive Bayes Algorithm

Below is the comparison table of accuracy for KNN, Logistic Regression and Naive Bayes Algorithm applied on WAZ (Weight for age Z score) or underweight, HAZ (Height for age Z score).

Sr.No.	WAZ/LAZ	Algorithm	Accuracy (%)
1.	WAZ	Logistic Regression	95.9
2.	WAZ	KNN	95.9
3.	WAZ	Naïve Bayes	95.4
4.	LAZ	Logistic Regression	94.8
5.	LAZ	KNN	94.3
6.	LAZ	Naïve Bayes	93.8

Table.1. Accuracy Comparison

5. CONCLUSION

These studies focused on using machine learning techniques to come across malnutrition in children beneath the age of 5. By reading information received from UNICEF and making use of Z ratings for weight and height, malnutrition cases had been recognized primarily based on a Z score threshold of -2. Various Machine Learning algorithms consisting of KNN, Logistic Regression, Naive Bayes, were taken in study. These algorithms had been capable of efficiently classify children as either malnourished or non-malnourished based totally on the provided dataset. The findings of this studies spotlight the capacity of gadget getting to know strategies in identifying and predicting malnutrition in kids. By leveraging these algorithms, healthcare experts and policymakers can develop greater accurate and green strategies for early detection and intervention, main aim to minimized malnourished children. However, it's crucial to observe that device getting to know algorithms are not a sufficient alternative choice to scientific assessment and diagnosis via healthcare experts. These algorithms should be used as supportive equipment in conjunction with expert knowledge and comprehensive assessment. Additionally, the overall performance and accuracy of the algorithms can also vary relying on the first-class and representativeness of the dataset used for schooling and checking out. Overall, the application of system getting to know strategies in malnutrition detection has the capability to contribute to better healthcare choice-making and aid allocation, in the long run main to stepped forward outcomes for youngsters liable to malnutrition. Further studies and improvement on this field can help refine and enhance the accuracy and effectiveness of those algorithms, in the long run benefiting the health and well-being of kids worldwide.

REFERENCES

1. WHO Multicenter Growth Reference Study Group. “WHO Child Growth Standards based on length/height, weight and age”. Acta Paediatr Suppl. 2006 Apr; 450:76-85. Doi: 10.1111/j.1651-2227. 2006.tb02378. x. PMID: 16817681.
2. Anaka Aiyar, Sunaina Dhingra, Prabhu Pingali, Transitioning to an obese India: Demographic and structural determinants of the rapid rise in overweight incidence, Economics & Human Biology, Volume 43,2021,101041, ISSN 1570-677X,
3. Sangita Khare, S Kavyashree, Deepa Gupta, Amalendu Jyotishi, Investigation of Nutritional Status of Children based on Machine Learning Techniques using Indian Demographic and Health Survey Data, Procedia Computer Science, Volume 115, 2017, Pages 338-349, ISSN 1877-0509,
4. Changes in Child Survival Are Strongly Associated with Changes in Malnutrition in Developing Countries, February 2003 Journal of Nutrition 133(1):107-19 DOI:10.1093/jn/133.1.107 4
5. Bitew FH, Sparks CS, Nyarko SH. “Machine learning algorithms for predicting undernutrition among under-five children in Ethiopia”. Public Health Nutr. 2022 Feb;25(2):269-280. doi: 10.1017/S1368980021004262. Epub 2021 Oct 8. PMID: 34620263; PMCID: PMC8883776.
6. SN Ariyadasa, LK Munasinghe, SHD Senanayake, NAS Fernando. “Data Mining Approach to Minimize Child Malnutrition in Developing Countries, Sri Lankan Context.” The International Conference on Advances in ICT for Emerging Regions-ICTer2012, Colombo, Sri Lanka.
7. G Deepa, K Sangita, A Ashish. “A method to predict diagnostic codes for chronic diseases using machine learning techniques”. Proceeding - IEEE International Conference on Computing, Communication and Automation, ICCCA 2016; 281-287.
8. Ruel MT, Menon P. “Child feeding practices are associated with child nutritional status in Latin

America: Innovative uses of the Demographic and Health Surveys”. J Nutr 2002, 32:1180-1187.
9. Sangita Khare, S Kavyashree, Deepa Gupta, Amalendu Jyotishi,” Investigation of Nutritional Status of Children based on Machine Learning Techniques using Indian Demographic and Health Survey Data, “Procedia Computer Science, Volume 115,2017, Pages 338-349, ISSN 1877-0509.
10. Ashis Talukder, Benojir Ahammed, “Machine learning algorithms for predicting malnutrition among under-five children in Bangladesh”. Nutrition, Volume 78, 2020, 110861, ISSN 0899-9007.
11. Shahriar, Md & Iqubal, Mirza Shaheen & Mitra, Samrat & Das, Amit. (2019). A Deep Learning Approach to Predict Malnutrition Status of 0-59 Month's Older Children in Bangladesh. 145-149. 0.1109/ICIAICT.2019.8784823.
12. Omer F Beser, Fugen Cullu Cokugras, Tulay Erkan, Tufan Kutlu, Rasit V Yagci “Evaluation of malnutrition development risk in hospitalized children” Nutrition Volume 48, April 2018, Pages 40-4.
13. Hatice Parsa, Aylin Açıkgoz, Beyza Doganay and Erdogan “Validity and reliability of the Turkish version of three screening tools (PYMS, STAMP, and STRONG-kids) in hospitalized children” Clinical Nutrition ESPEN, Volume 39, October 2020, Pages 96103
14. Cynthia Hayat, Barens Abian, “The Modeling of Artificial Neural Network of Early Diagnosis for Malnutrition with Backpropagation Method”, 2018.
15. Baraybar-Huambo, Juan & Gutiérrez-Cárdenas, Juan. (2020). SCUT Sampling and Classification Algorithms to Identify Levels of Child Malnutrition. 10.1007/978-3-030-461409_19.
16. Z. Momand, P. Mongkolnam, P. Kositpanthavong and J. H. Chan, "Data Mining Based Prediction of Malnutrition in Afghan Children," 2020 12th International Conference on Knowledge and Smart Technology (KST), 2020, pp. 12-17, doi: 10.1109/KST48564.2020.9059388.
17. Kishore, K. Krishna, Jami Venkata Suman, I. Lakshmi Mnikyamba, Subba Rao Polamuri, and B. Venkatesh. "Prediction of malnutrition in newborn Infants using machine learning techniques." (2023).