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Research paper

An Enhanced Machine Learning Approach for Early Detection of Malnutrition in Toddlers, Using Health and Social Determinants Data

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Abstract

National progress and its global standing start with the health of the early-age population. The well-nourished children have become skilled, constructive, and efficient resources to make innovative establishments. This will lead their country to be stronger and more successful in the global economy and its overall well-being. Many countries like India, Japan, the US, Germany, South Korea, and Switzerland started to invest in children's health care and early education systems. The Indian government has implemented several schemes and plans to prioritize child health care to be more competitive globally. Still, child malnutrition remains one of the challenging issues due to its vast population and cultural differences. These challenges will be rectified by monitoring the child's nutrition status with powerful actions and plans. The machine learning models were helpful in various sectors of decision-making mechanisms. This paper implemented the enhanced machine learning model to detect the malnutrition status of children up to 5 years old. The malnutrition status can be measured by several indicators. This model takes diet routine, socio-economic status, family type, health check-up routines, vaccination routines, exclusive breastfeeding, demographic data such as gender, age, and anthropometric measures such as height and weight to estimate the nutrition status of the toddlers. The enhanced machine learning model combines the results of the Support Vector Machine, Logistic regression, Gaussian Naïve Bayes, and Random Forest machine learning models to produce an output with 94% accuracy, demonstrating the problem using real-world instances.

Keywords: *Enhanced; Machine; Malnutrition; Data; Health.*

1. Introduction

The early childhood stage is a crucial part of the journey of one's life. Since it lays the foundation for the physical, intellectual, and emotional development of a human being. This early childhood can be categorised into three segments:

1) 6 months to 1 year – Infancy
2) 1 year to 3 years – Toddler
3) 3 years to 5 years – Pre-school

Observing these stages, there is a drastic change in both the physical and mental growth of the child. For example, motor skills like crawling and sitting in the infancy stage become fine motor skills like drawing, painting, building blocks, and gross motor skills like jumping, running, and climbing in the pre-school stage.

The environmental or biological elements can influence the cognitive, physical, and social development of the child. Sometimes, both elements cause critical changes in their development, either in the short term or the long term. These elements include maternal health, birth complications, nutritious food, parenting method, genetics or family medical history, access to resources, peer group, lifestyle, play routine, early education, and socio-economic status of the family.

The United Nations Children's Fund (UNICEF) examines child malnutrition and its wide range of effects. UNICEF is a global organization that operates on the nutritional enhancement of children in many countries where undernutrition is common. It concentrates on both short-term and long-term issues of malnutrition in children.

The short-term consequences are:

1) Immune system weakness.
2) Low energy levels to do day-to-day activities.
3) Delays in physical and cognitive growth.
4) Slower recovery from wounds.
5) Reduced red blood cell counts.

6) Difficulty in cognitive knowledge, like concentration, learning, and memory.

The long-term consequences are:

1) High risk of chronic diseases like diabetes, heart disease, and hypertension.
2) Permanent physical growth reduction.
3) Low IQ levels.
4) High chances of infections due to a weakened immune system.
5) Fertility issues.
6) Organ failures.

Both issues of malnutrition affect an individual's overall health, cognitive, physical, and emotional development. It is important to identify the malnutrition status in early childhood to prevent long-term health issues, mortality, and enhance development. This will lead to a healthy and wealthy nation in the future.

There are many predictive models developed to predict the nutrition status and its severity. These predictive models were developed by applying machine learning algorithms to historical or real-time datasets.

Benefits of predictive models in malnutrition prediction systems:

- Prediction systems: multiple machine learning algorithms were used to build the malnutrition prediction systems to identify the machine learning model with high accuracy.[21]
- Early warning system: The machine learning algorithm is used to identify the current poverty level and malnutrition to provide early warnings. This can help prevent future health issues with the mapping of resources.[22]
- Personalised recommendation system: the predictive model helps to address the more vulnerable populations at risk of malnutrition and recommends special treatment to prevent them from malnutrition attacks.[23]
- Integration of data: The machine learning-based predictive models integrate multiple varieties of data like age, region, wealth index, education status, marital status, drinking water facility, toilet facility, and type of cooking fuel, to predict malnutrition. [24]
- Incorporation of other risk identification: The machine learning algorithm adopts the malnutrition prediction system to predict the factors influencing other diseases like anaemia in children.[25]
- Decision-making support: the malnutrition prediction system supports the healthcare providers in making decisions on their treatment process, treatment priority, nutrition supplements, identifying special needs, etc. [23]

2. Literature review

The rural areas of Tamilnadu have the right to receive unbiased health care services and infrastructure. But it is crucial to execute in every rural area. The rural areas deal with many challenges. Such as geographic locations, a lack of awareness about the pre-emptive healthcare procedures, a shortage of funding, and limited healthcare service providers. The synergy of government authorities, Non-government Organizations (NGOs), private organizations, and institutions will help the Government to increase human resource development and awareness about health care services, sanitation, maternal health, child health, and remote health care services. By tackling these issues, the nation will notice significant outcomes in citizens' health and in the growth of socioeconomic activities. Contribution of funding to the rural health care services is both an intelligent investment and a moral responsibility for the prospective wellness of Tamil Nadu people.[1]

The National Programme for Maternal and Child Health (NPMCH) was initiated on oct 7,2005 to reduce the Maternal Mortality Rate (MMR) and Infant Mortality Rate (IMR) in India. This programme includes the benefits of antenatal care for pregnant women, ensuring safe delivery, postnatal care for children and mothers, child health care, and reproductive health care services. Various challenges are faced by pregnant women. These challenges include poor nutrition, abortion, anaemia, and prior LSCS. These risks can be recognized during the first visit of the health care service providers.[2]

Pregnant women belonging to underprivileged societies are highly vulnerable to maternal mortality and post-maternal mortality. They didn't get enough calories from their food. The underprivileged women are not well off in their socioeconomic status. They work for daily wages to meet their fundamental needs. These mothers could not afford the nutritious foods they needed to fulfill their family's daily essentials.[3] According to the health assessment guidelines of the American Academy of Pediatrics and the Child Health and Disability Prevention (CHDP) program, precise and continuous anthropometry values facilitate the recognition of health-related, nutrition-related, and community-related problems in children. Since these anthropometry measures also help to identify the nutritional status of pregnant women, the growth of the child will be assessed and treated in the early stage.[13] The Government of Tamil Nadu introduced Dr Muthulakshmi Reddy's Maternity Benefit scheme in the early 1990s. This scheme is aimed at supporting underprivileged women financially. This financial support will help them to take nutritious foods and recoup their loss of wages during their maternity period. The tracking system PICME was launched to monitor the child and mother's health from the early stages of pregnancy to their 5th year. This tracking system ensures that every mother and child receives the immunization service provided by the Government. The PICME merged with Dr. Muthulakshmi Reddy's Maternity Benefit scheme in 2012. It helps the mother to claim their cash benefit once she registers with the PICME. In 2017 PICME scheme was upgraded with the features of the Civil Registration System (CRS) software as PICME 2.0. This scheme achieved over 99.4% of birth registration. The 108 ambulance service is offered for pregnant women free of cost. This toll-free ambulance service serves the underprivileged pregnant women to reach the hospital as soon as possible in emergency instances.[3]

The central government incorporates Pradhan Mantri Matru Vandana Yojana (PMMVY) with Dr Muthulakshmi Reddy Maternity Benefit scheme (MRMBS) as a 60:40 sharing with the state government. The eligible mother receives Rs.8,000/- under PMMVY-MRMBS, and the remaining Rs.. 10,000/- will be paid through MRMBS. This includes 2 nutrition kits worth Rs.4,000/-. The table below (Table 1) shows the functions of PMMVY-MRMBS benefits.[4].

Table 1: Pradhan Mantri Matru Vandana Yojana (PMMVY) with Dr Muthulakshmi Reddy Maternity Benefit Scheme (MRMBS) Benefits

Number of instalments/kind of benefits	Prerequisite	Value (in Rs.)
I Instalment	Antenatal registration on or before 12 weeks	2,000
Kind benefit I	First Nutrition Kit	2,000
II Instalment	After 4 months	2,000
Kind benefit II	Second Nutrition Kit	2,000
III Instalment	After delivery in Government Hospital	4,000
IV Instalment	For those received 3rd instalment	4,000
V Instalment	For those received 4th instalment	2,000
Total		18,000

The nutrition kit includes Health Mix Powder for Pregnant Mothers - 1kg, IFA Syrup – 3 Nos, Dates – 1kg, Protein biscuits – 500 gms, Aavin Ghee – 500 gms, T. Albendazole – 3 Nos and Towel – 1 Nos. [5]

Women's education plays a vital role in the socio-economic development of a country. The literacy rate among rural women and rural men is significantly higher in Tamil Nadu. A specific approach is needed to resolve this problem. The government agency called the Tamil Nadu Corporation for the Development of Women (TNCDW) was launched in 1983 to strengthen women's socio-economic activities. It encourages women to be self-employed and entrepreneurs. The saving practice is encouraged by creating Self-Help Groups (SHGs) in rural areas. It also allows them to access the nearby banks and sets them free from the neighbourhood micro-lenders. These SHGs are implemented in association with banks and NGOs. This scheme helps them to be aware of the importance of women's education.[6]

SDG 2030 encourages ending all kinds of poverty, ending hunger with food security and better nutrition, and guaranteeing a healthy life to promote the well-being of all humans. SDGs are fulfilled by speeding up the action on the socio-economic factors and the empowerment of women worldwide. By achieving the SDGs, maternal mortality, infant mortality, and stunting conditions in children under five years will be diminished. Many countries need to take prior actions on Reproductive, Maternal, Newborn and Child Health (RMNCH) to reach the SDGs.[7]

The equitable distribution of resources to all kinds of people will boost the economic standard of the nation. The proper enhancement of the legal framework elevates the factors related to a child's nutritional status. The process of strengthening the family's economic condition empowers the well-being of the family and reduces the malnutrition of the children. It is possible by creating new jobs and microfinance assistance, providing quality and affordable education, easy access to health care services, and tax relief to low and middle-income families. Less nutritional knowledge leads to insufficient, irrelevant nutrition, under-nutrition, and other challenges to children's health. To resolve these issues, the government needs lots of experts to create awareness among the different communities of people.[8]

A considerable amount of children thrive in early malnutrition even in limited resource environments as a consequence of Pre-emptive measures. Still, many children are affected by Neurological development. They exhibit low IQ, poor performance in schools, and conduct disorders throughout their life.

Malnutrition is common in developing countries. Only a few studies evaluated the structure and functions of the brain through electroencephalography (EEG) and evoked potentials (ERP), which are low-cost methods. In most developing nations, the advanced methods in neuroimaging, such as functional near-infrared spectroscopy (fNIRS) and magnetic resonance imaging (MRI), are not affordable and have limited Accessibility. Therefore, it is important to assess malnutrition at the point of neural development as well. It helps policymakers create new strategies to predict, classify, and treat the affected children with malnutrition.[9] Humans realize their capacity through the propagation and maintenance of their early childhood.[10]

The Triple Burden of Malnutrition (TBM) is described as over-nutrition, under-nutrition, and micronutrient deficiency. The study shows that India suffers from this Triple Burden of Malnutrition (TBM). The TBM is linked with various factors. Such as intake of low-nutrient foods, culture, absence of sanitation, unhygienic feeding practices, clean water scarcity, fewer health care services and infrastructures, and improper implementation of nutritional schemes of the government. Various research confirms that the nutritional deficiency of children under 5 years affects their physical and Psychological health permanently. The government initiated multiple nutritional schemes for the children via the Anganwadi centres and the schools (with the help of the Department of Education). The problem of TBM should be considered as the first and foremost problem to be resolved in the political aspects.[11]

The studies illustrate that malnutrition in paediatrics is prevalent. Pediatric malnutrition should be diagnosed for educational and research purposes and cured for the sake of child health development. Even one child's health influences the whole society's health. Considering these complications, the diagnosis and fis of pediatric malnutrition is Paramount.[12]

Disease Control and Prevention suggests that an anthropometric measure plays a significant role in the process of malnutrition prediction in children and adults. Anthropometry indices are commonly used measures to identify the health status, nutritional deficiency, and growth pattern of the child. A child's developmental pattern describes overall wellness. The basic anthropometry measures are height, weight, and body mass index.[13]

Though less nutritious food and infectious diseases are the major reasons for child malnutrition, the gut microbiota plays a crucial role in causing malnutrition in children. The gut microbiota simulates the functions of the immune system, digestive system, metabolism, and psychological functions. In the immune system, the gut microbiota defends against pathogens and regulates inflammatory responses. The gut microbiota breaks the carbohydrates and fibre and supports the nutrient absorption functions in the digestive system. The mental health and mood are determined by the gut microbiota. The gut microbiota helps to generate vitamin K and B vitamins and Short-Chain Fatty Acids (SCFAs), which help the functions of metabolism. The pathogenic element of gut microbiota simulates diarrhoea, and it is the key participant in creating malnutrition among children. Diarrhoea causes absorption disorders, and it leads to weight loss.[14]

Inadequate or surplus amount of one or more nutrients creates dysfunctions in the body and lead to malnutrition. Nutrients consist of macronutrients such as carbohydrates, proteins, and fats (help to create energy and build the body) or micro-nutrients, minerals, and vitamins (help in the functions of the body). One-fourth of the children in the world are affected by stunting because of undernutrition or obesity. Anaemia and iron deficiency are commonly occurring diseases. It affects around 50% of the pre-school children and one out of three women in her fertile age. Most countries face these types of malnutrition among children. Diarrhoea causes less consumption of food, increased needs of the metabolism, and nutrient loss.[15]

The scant nutrient intake causes malnutrition, and this may implicate failing to receive sufficient vitamins, calories, minerals, fat content, and carbohydrates to the human body. Malnutrition in kids triggers chronic kidney disease, heart anomaly, liver disease, and cystic fibrosis syndrome.[16]

Many interventions have been taken for malnutrition and overnutrition worldwide. Most of the interventions are directed through the health sector. But it should be implemented through education, agriculture, water, sanitation, and welfare programs as well. Overnutrition relates to non-communicable diseases (NCDs) - diabetes, hypertension, and coronary heart disease. To avoid these conditions and create a healthier world, facilitate the surroundings by consuming healthy foods such as fruits and vegetables, as well as reducing the consumption of meats and highly processed foods.[15]

In the 1990s, India achieved a decent reduction of under-nutrition status, still it was less compared with other countries with the same economic growth of economics. This is due to different cultural practices and geographical locations of the states of India. The ICDS program deals with the factors that affect the nutritional status of the children. Even though the ICDS program was well-crafted and implemented, the void between the design and deployment is unavoidable in India. The constant actions on this program fulfil the real intention.[17]

It is important to create new strategies and interventions in the preconception phase to enhance the outcome of the pregnancy. It supports the society to have healthy childhood development, improve metabolic health, and decrease the risk of chronic diseases.[18]

The health care services and nutrition services are fundamental necessities for the development of early childhood. The nourishing care for mothers and child care must be reasonable and flexible to access. In low and lower- and lower-middle-income countries, 43% of children belonging to aged five are more vulnerable to stunting and poverty factors. It affects their physical, emotional, and cognitive growth. The prioritization of early childhood development builds a country with healthier and more productive communities.[19]
Advanced research, policies, and schemes elevate the existence of life and development. These actions should be implemented by every child who should access the nourishing care without negating any child. The proposed conceptual framework for children with endurance and growth has three components. Such as distal factors include policies, ideologies, economics, and climate, enabling environments include families and society, and proximal components include health care services, nourished food, education, safety, and security. With the completion of these components, the child will survive and succeed in their life.[20]
The statistical method and machine learning method are assessed to find the best approach to identify the malnutrition of children in Somalia.[31] The statistical model applied a regression equation to find the stunting status of the child in India.[32] This study utilizes different machine learning algorithms to find the malnutrition status of children between the ages of 0-5. The random forest classification model achieved the highest accuracy.[26] The random forest classification algorithm performed well in the malnutrition prediction of children in Bangladesh.[27] The machine learning algorithm detects the child's malnutrition across different countries through Demographic and Health Surveys (DHS) data.[28] Also, the Indian Demographic and Health Survey (IDHS) dataset was employed to detect the features related to anaemia through machine learning techniques. [30] The malnutrition prediction of the newborn was determined by the z-score and included age, height, weight, and gender as predictor variables. This model inherits the dataset from the UNICEF organization. The proposed model takes target variables with two classes, such as underweight and stunting. Among the five ML algorithms (KNN, naïve Bayes, SVM, logistic regression, and ANN), the logistic regression machine learning model provides better results than the other models.[29] In contrast, the proposed decision tree model achieved 92% accuracy in malnutrition classification, compared to other classification algorithms – SVM, KNN, random forest, and GBM classifier.[33]
Throughout this literature, it is visible that nutrition is important for human life and societal development. The early detection of nutritional deficiency can reduce the issues related to malnutrition. The government planned and executed the policies and schemes to overcome these malnutrition problems. Still, some regions of the child are affected due to various reasons. Those regions are to be monitored regularly through statistical or machine-learning models. Only a few models were implemented to detect malnutrition in toddlers. The strong models need to be trained with real-time data to get appropriate outcomes. Especially in India, advanced machine learning models are required to detect malnutrition due to cultural and geographical differences.

3. Methodology

The proposed methodology follows a structured approach to find the malnutrition status of the toddlers. This approach begins with the data collection process to build the predictive machine learning model.
Data Acquisition: The dataset was sourced from two different fields to depict the complete picture of the problem. The primary and secondary datasets were collected from two fields and merged to bring the unabridged dataset for model implementation. The primary dataset is obtained through the survey questionnaire from the child’s mother, and the secondary dataset is obtained from the Anganwadi centres from various places. The common variables such as name, gender, and DOB were identified and aligned to verify that the secondary and primary data have been properly integrated.
Dataset – Description: This dataset holds records of the children at the age of 0 to 5 years, which is used to predict the malnutrition status. The primary dataset contains name, gender, DOB, age, exclusive breastfeed, vaccinations, quality diet, socio-economic status, mother’s education status, type of family and regular health check-ups. The secondary dataset contains name, gender, age, height, weight and malnutrition status.

Table 2: Dataset Description

Feature name	Description	Type	Values
Name	Name of the child	String	Alphabets
Gender	Gender of the child	Categorical	Male/female
Age	Age of the child	Integer	0-5
DOB	Date of Birth of the child	Date	Date
Exclusive Breastfeed	The child is exclusively breastfed until 6 months of age	Categorical	Adequate/ Not adequate
Vaccinations	All the vaccinations taken timely	Categorical	Yes/No
Quality Diet	The child is taking a quality diet regularly	Categorical	Yes/No
Socio-Economic Status	socio-economic status of the child’s family	Categorical	Rich/Upper Middle Class/Middle Class/Lower Middle Class/Poor
Mother’s Education Status	The education status of the child’s mother	Categorical	Literate/Illiterate
Type of Family	Child’s family type	Categorical	Joint/Nuclear/Single Parent/Under Guardian
Regular Health Check-ups	The child's health check-up is taken regularly	Categorical	Yes/No
Height	The height of the child (in cm)	Integer	Numerical
Weight	The weight of the child (in kg)	Integer	Numerical
Malnutrition Status	Malnutrition status of the child	Categorical	Normal/SAM/MAM/Overweight/Obesity

Data Exploration: Data exploration is one of the essential steps to identify the patterns of the dataset and also to improve the quality of the data. This process helps to enhance the data pre-processing. The dataset contains Name, Gender, Age, Exclusive breastfeeding, Vaccinations, Quality diet, Socioeconomic status, Mother’s education status, Type of family, regular health check-ups, Height, Weight as the independent attributes, and Malnutrition status as the target variable. The target variable is the categorical type, which consists of five types of categories – Normal, SAM (Severe Acute Malnutrition), MAM (Moderate Acute Malnutrition), Overweight, and Obese. The below image (Fig. 1) describes the distribution of Malnutrition status types in the dataset.

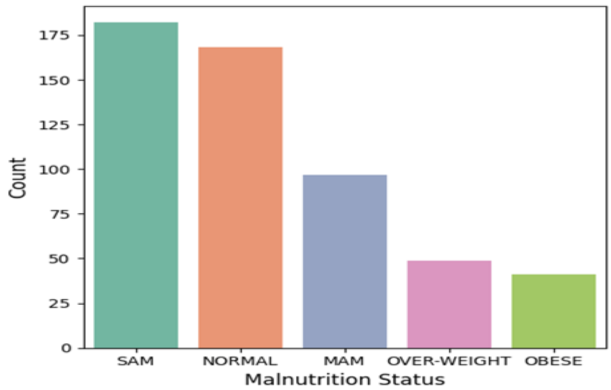

Fig. 1: Distribution of Malnutrition Status.

Data Pre-Processing:Data pre-processing is the key step in designing the machine learning model with efficiency and accuracy. To ensure the reliability of the model, the irrelevant attributes should be eliminated. This dataset holds irrelevant variables such as the name and DOB of the child. These two attributes are removed from the dataset. The categorical variables have been encoded as numerical values using label encoders. The dataset was split into a training set and a testing set with a 4:1 ratio. The training set will be used to train the machine learning model, and the testing set will be used to test the performance of the model. The training and testing features are standardized as this dataset is used in the SVM classification algorithm. It is important to scale up the features before sending to the SVM.

Support Vector Machine Algorithm:The support vector machine follows the supervised learning technique. It is capable of handling both regression and classification problems. Still, it is suitable for classification tasks. The SVM algorithm creates a hyperplane in multi-dimensional space to classify the data into different categories. The best hyperplane is chosen with the highest margin, which is called the hard margin. The margin is calculated based on the distance between the support vectors and the hyperplane. The hard margin separates the classes without any misclassifications. In the existence of outliers and non-classifiable data, the support vector machine provides soft margin classification with some misclassifications. It allows the kernel function for non-separable data to view the data points in higher higher-dimensional space.

Logistic Regression Algorithm: The logistic regression involves statistical analysis to discover the relationships among the given variables. It is a supervised machine learning algorithm, and it is used for classification analysis purposes. The classification can be binary classes, multiple classes, or ordinal classes. It follows the basic principle of logistic regression. The sigmoid function takes the independent variables as the inputs and predicts the probabilities as output. The probability values are between the range of 0 and 1. It provides the real numbers, and the output categories can be predicted based on the given threshold value. This sigmoid function forms the curve in the shape of “S” which means the output values could not go beyond 0 to 1. Once the regularizations are done with the features, it will be easy to implement, and it will avoid overfitting.

Naïve Bayes Algorithm: Naïve Bayes algorithm is a supervised machine learning algorithm. It handles the classification tasks with the help of Bayes' theorem. It also finds the probabilities like logistic regression through the Bayes theorem. The probabilities decide the classes of the target variable. It determines the output category of the given dataset. The Naïve Bayes algorithm follows the variable independence in the input data. It means the existence of one variable doesn’t affect the other variable's values, and it does not have any relationship among them. Gaussian Naïve Bayes is one of the types of Naïve Bayes algorithms. It applies normal distribution among the variables by mean and standard deviation. This distribution is also called the Gaussian distribution. It calculates the likelihood of input data fitting the category in the target feature. Though the Gaussian NB could not find the complex relationship of the features, it works well with the irrelevant features to find the solution.

Random Forest Algorithm: The random forest algorithm is a type of ensemble learning. It builds multiple decision trees to predict the output of the given data. It improves the accuracy by randomly picking up the data from the dataset and feeding this data to the decision trees as input. Those decision trees work without any dependency, which means each decision tree is trained with a distinct portion of the dataset. The results of each decision tree will be combined, and based on the voting process, the whole result will be derived. The classification problem needs a voting technique to select the high-accuracy result. The random forest algorithm handles large datasets since it can create many decision trees with precise decisions. It avoids the problem of overfitting while it constructs multiple decision trees.

4. Proposed model

The proposed model combines multiple machine learning algorithms to implement the enhanced ensemble machine learning model. This proposed machine learning model integrates multiple perspectives of the problem and generates the final solution to enhance the performance of the model. Support vector machine, Logistic regression, and Gaussian Naïve Bayes algorithms were used to build the base model. The Meta model was implemented using the Random Forest algorithm. The training dataset was taken as the input to these base models. The base models were trained to map each input data to the prediction variable labels.

The i^{th} data point from the n^{th} model was alignedto the predicted label$\hat{y}_i^{(n)}$. These predicted labels were collected for each instance of the dataset for each model. Those prediction labels $P_i = \hat{y}_i^{(1)}, \hat{y}_i^{(2)}, \ldots \ldots, \hat{y}_i^{(n)}$ were fed to the random forest classifier model as the input data. The meta-model navigates the input data points P_i to the predicted label$\hat{y}_i$.

$$\hat{y}_i = f_{meta}(P_i)$$

This Meta model trains by obtaining the actual output values $y_i = l$ where, $l \in \{0,1,2,3,4\}$ from the training dataset d_{train} . This process will enhance the accuracy of the machine learning model. It is done by minimizing the difference between the actual and predicted labels with the help of the cross-entropy loss function.

$$\mathcal{L}(\theta) = \frac{1}{d_{train}} + \sum_{i=1}^{d_{train}} 0 \sum_{l=0}^{l-1} I\,(y_i = l) \log \mathbb{P}(\,\hat{y}_i = l \parallel P_i; \theta)$$

The loss function $\mathcal{L}(\theta)$, ensures that the proposed model finds the optimal parameters θ. Hence, the final predicted outputs $\hat{y}_i$ were mapped with the actual labels y_i with maximum precision.

$$\hat{y}_i = f_{meta}(\hat{y}_i^{(1)}, \hat{y}_i^{(2)}, \dots \dots, \hat{y}_i^{(n)})$$

The meta-model gives the final predicted class$\hat{y}_i$ using the input data, such as base model predictions P_i and training dataset d_{train}. The random forest classifier model helps to balance both the performance and interpretability of the proposed model. Once the training process is completed, the model receives the test dataset to predict the final output.$\hat{y}_i$. This testing process is essential to calculate the accuracy metrics such as precision, recall, support, accuracy, and f1-score. These accuracy metrics determine the performance level of the classification model.

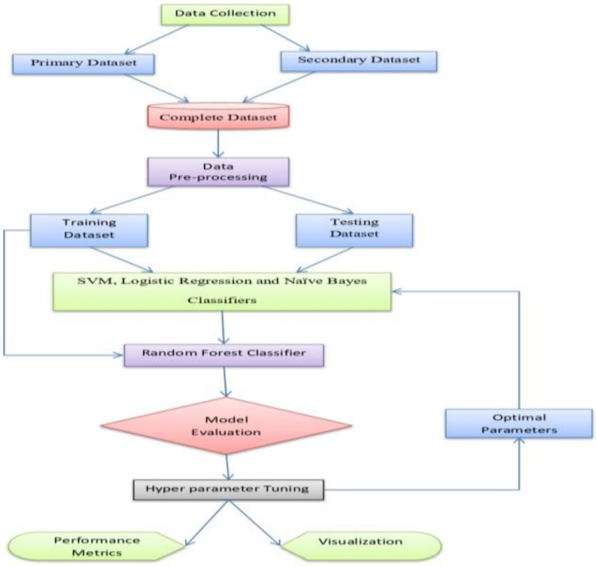

Fig. 2: Architecture Diagram of Proposed System.

5. Results and insights

The correlation matrix helps to identify the relationship among the attributes of the dataset. This diagram represents the dataset in a simplified version, which leads to improved decision making.

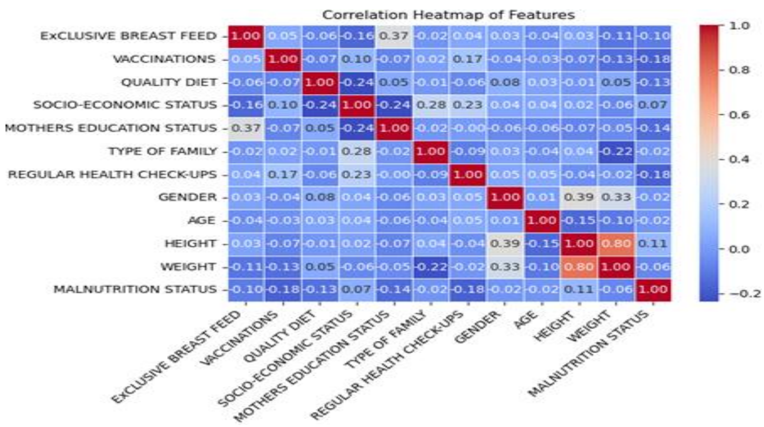

Fig. 3: Correlation Matrix.

The predictor attributes, such as vaccinations, regular health check-ups, age, diet quality, mother's educational status, and exclusive breastfeeding, show moderate and slight positive correlations with the target variable – malnutrition status. The correlation matrix (Fig. 3) says that the child who is affected by malnutrition is taking vaccinations and health check-ups regularly. The child with a proper diet and exclusive breastfeeding is nourished and healthy. The mother's good educational status also reflects the well-nourished children. The attributes, socio-economic status, height, and weight depict the negative correlations with the malnutrition status. Higher socio-economic status, height, and weight are the most likely of well-nourished children. The above interpretations show that each attribute plays a vital role in predicting the malnutrition status of the child.

The proposed ensemble model utilizes various ML algorithms to build an improved and efficient machine learning model. This model interrogates the problem from diverse angles by implementing several learning techniques. These techniques facilitate to construction of the Meticulous and accurate prediction model. This model preserves the strength of each machine learning algorithm while alleviating its limitations which makes the model more robust and comprehensive. The proposed model achieved an overall accuracy of 94%, with higher precision, recall and F1-scores for each class. Thus, the model exhibits working on complex data patterns with higher accuracy and reflects the same accuracy on real-world applications which enhances the reliability and error-reduction. The result table (Table 3.), classification report (Fig 4.) and confusion matrix(Fig 5.) tell that the proposed model performed well with all classes with consistency.

Table 3: Result Table

Class	Precision	Recall	F1-Score	Support	Accuracy
0 (Normal)	0.94	0.91	0.93	34	
1 (MAM)	0.96	1.00	0.98	45	
2 (SAM)	1.00	0.79	0.88	14	94%
3 (Over Weight)	0.82	1.00	0.90	14	
4 (Obese)	0.94	0.93	0.94	55	

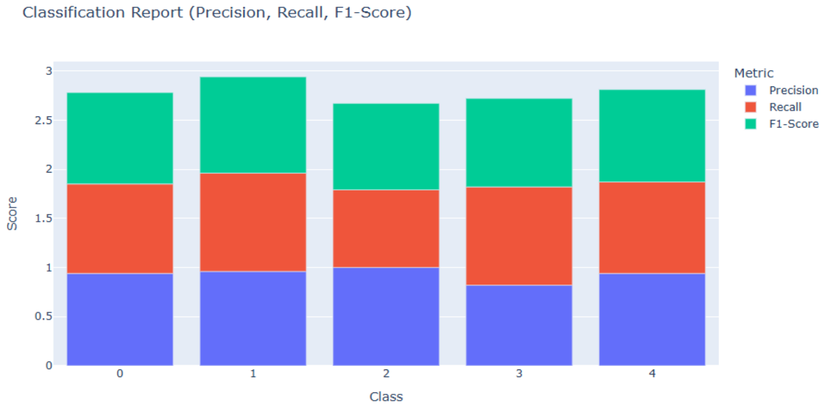

Fig. 4: Classification Report.

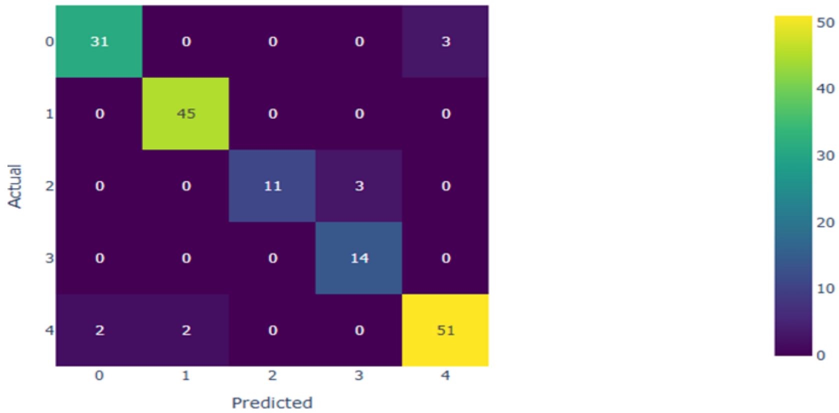

Fig. 5: Confusion Matrix.

6. Conclusion

The detection of malnutrition at an early age helps the children to their better growth and development both physically and mentally. It also prevents the children from the risk of chronic diseases and supports the immune system and brain development. This paper highlights the importance of early detection of malnutrition in children within the age of 5 years. Numerous factors affect children with malnutrition. This study analyses the internal factors which are primarily used to measure malnutrition and the external factors that force children to be malnourished. In future, Well-nourished children build a society with improved health and wealth. In this case, introducing machine learning algorithms to predict the malnutrition status of the children will elevate child health care and it will accelerate children to be more productive in their adulthood. The machine learning model identifies the important features to predict malnutrition and classify the malnutrition status of the child into five categories with 94% accuracy. Compared to existing methods, this machine learning model introduced four machine learning models to be combined and produced the output. This proposed machine learning model outcome analyses multiple factors which cause malnutrition directly and indirectly. This machine learning model alarms the policymakers to address malnutrition and recognize the significant factors which cause malnutrition. Ultimately, a well-nourished society is accomplished by collective awareness and proper implementation of policy interventions.

7. Future enhancement

The machine learning model outcomes can be more generalizable when it deals with larger and different sets of data. In future, the model can be implemented with explainability techniques to provide more transparency and trust towards its operation and prediction to the healthcare workers. Wearable devices and mobile apps can also be incorporated to detect the child's malnutrition level and treat them accordingly. It enables the model to be a continuous monitoring system and early warning system for real-time applications.

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