Grenze International Journal of Engineering and Technology, January Issue

# A Non-Invasive Approach for Prediction Malnutrition: the power of AI & Health Care Technology

Namrutha.D[1], Jaya Lakshmi.CH[2], Pranitha.R[3] and Mahesh Babu B[4]
[1-4]Department of Electronics and Instrumentation Engineering, Siddhartha Academy of Higher Education Deemed to be University, Vijayawada and 520007, Andhra Pradesh, India
Email: 1228w1a1068@vrsec.ac.in, 2 228w1a10a2@vrsec.ac.in, 3 228w1a1063@vrsec.ac.in, Vijayawada and 520007, jayalakshmichandra@vrsiddhartha.ac.in

***Abstract*— Body fat and hydration are two health signs that impact on how our body works, how active we feel, and our prospects of long-term diseases. Severe dehydration may be life-threatening; even mild dehydration may make us feel tired or affect our mind. Abnormal levels of fat are also linked to problems such as heart and metabolic diseases. The traditional methods of measuring fat and hydration are not exactly comfortable: they are expensive, cumbersome, and extremely time-consuming. In this study, we investigate the new methods of measuring body fat and hydration using IoMT in a painless manner and in real time. To enable the doctors to act fast, for the model to be interpretable and thus easy to comprehend, we investigate new sensors, machine- learning models, and explainable AI methods.**

***Keywords*— Sensor, Arduino Uno Board, Random Forest, Malnutrition.**

## I. INTRODUCTION

Malnutrition is a quiet crisis that has impacted many children in poor countries. Malnutrition has serious physical and emotional consequences for the youngest and the poorest group. In addition to the enormous suffering that it causes, malnutrition slows a nation's progress: it reduces productivity, the burden on hospitals increases and people do not live up to their potential.

Even as India grows rapidly in the economy, education and technology, it has not been able to escape this problem One third Of the world's undernourished children can be found in India. Astonishingly, a million babies die before completing a month of life. Nearly one- third of India's are malnourished. Currently ,48 percent of all children under five are stunted, while 43 per cent are underweight. The situation is worsening [1].

As per various government surveys such as NFHS-3 and NFHS-4, there is marginal improvement as seen in some areas. Schemes such as ICDS offer nutrition counseling along with care but they suffer from poor implementation, general lack of awareness and adequate information among caretakers. A significant number of pregnant and lactating women do not get adequate nutrition counseling for better women's health and infant's health [2] ………

Malnutrition is not limited to India, but it has taken over most of South Asia, including Bangladesh and Pakistan; this is since more than 50 percent of the children in this region have poor nutrition and that more than 165 million children around the world were stunted in 2015 alone [3].

*Grenze ID: 01.GIJET.12.1.580_1*

Absolutely India must have made some gains around child nutrition from 1998 to 2020. Underweight children have decreased, and percentage of stunting has dropped from 48% to 35.5%. But there is still a lot to be done. Anemia in women has gone up from 51.8% to 57% and severe wasting in children remains very high [1].
Malnutrition is not just hunger. It makes children weak, vulnerable to disease. They are more likely to fall ill with diarrhea, pneumonia, tuberculosis diseases that still cause almost a third of all deaths among young children, along with malnutrition itself [4]. The other big problem is the double burden of malnutrition: undernutrition and over nutrition, causing obesity and related diseases. Both pass from mother to child and on through the generations. Each adds more danger.
We need to act now and not feel sorry for each other. Food must be given a high priority in the plans of the government especially for women and children with better food, education and access to health care services [5]. Treating malnutrition is not only nice but it is also a good investment in the future of the world. The failure to act will leave the future of millions of children in jeopardy and will jeopardies social well-being and economic stability worldwide [3].

## II. Literature Survey

Today, child malnutrition is still the biggest health problem. Issues in the world, especially in developing countries. A new study conducted by UC Berkeley researchers at UCSF published in Nature 2022 highlights the critical period in a child's early years. The study found that babies who first slowdown in six months after they were born are at a significantly higher risk of severe malnutrition and premature death. The result of the study provides solid basis for women of childbearing age to make special interventions even preconception by preventing irreversible damage to the developing brain [6].
More than 45 million children are currently suffering from wasting and 150 million more from stunting as of 2022. A large-scale study of 84,000 children in 15 countries, including South Asia and Sub-Saharan Africa, regions showed that more than a million deaths a year are due to wasting and stunting caused by malnutrition [7]. Undernutrition, micronutrient deficiencies and seasonal food insecurity affect children's health outcomes significantly, according to the World Health Organization, where maternal nutrition is poor [8]. Even with targets like the Zero Hunger goal for 2030 or the aim of the Global Nutrition Report to eliminate 40% of stunting in children by 2025, much more needs to be done. If we continue to do what we do now, more than 660 million people will remain undernourished by 2030 [9]. Seasonal influences, such as the month a child is born, can contribute to malnutrition in South Asia. Children born in May are more likely to waste away due to conditions like lack of food and fluctuating rainfall [10].
It is alarming that once again, so many forms of malnutrition are passed down from one generation to the next. Malnourished children whose mothers were undernourished are likely to be undernourished as adults. "Early combined efforts in maternal health, infant care, and well- supported public health interventions are needed to break the cycle," says Andrew Mertens of UC Berkeley [11]. Altogether, these studies tell us that we need to fight malnutrition with an approach that connects nutrition counseling, better maternal and child health, sufficient food for families, and community involvement. Otherwise, the futures of tens of millions of children, and even entire countries, are at risk if we do nothing.

## III. Research Gap

Even with better sensors and AI, the models that are commonly available return inaccurate results (even when achieved in real-time), are unintelligible and untrustworthy. Most models are accurate but don’t Tell you how the prediction was made which lowers trust (especially critical in health-related applications). This is exacerbated by the absence of common models, low-cost deployment options and ease of use with wearable/satellite data. As would be seen from the comparison table, only the Random Forest with Ensemble returned an accurate result of 96%, the rest was garbage. Very big issues that need to be addressed so intelligible, low cost and scalable solutions can be created that will empower communities to tackle their malnutrition problems.

## IV. Comparision Table

Different machine learning models were tried out, with the use of non-invasive sensors which are accurate and reliable in predicting malnutrition. The comparison shows how each model will perform and which ones are more suitable for real healthcare. Among all the models, Random Forest Ensemble is the best because it is most accurate with an accuracy of 96 and it is clear while explaining.

The most important thing is that the system not only predicts well but also it explains the process of how it predicts it. This is very important for the user as well as healthcare workers. The most understandable is Decision Tree but it is not accurate and it over fits which may lead to unstable behavior in real situation.

Easiest model is KNN, but it is sensitive to noisy data which leads to decrease in accuracy. Easy to use, Logistic Regression is accurate when the data is simple like straight line pattern but when the data is complex like real health data there is no straight-line pattern, so it fails to work.

TABLE I. COMPARISON TABLE

| Model | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) |
|---|---|---|---|---|
| Random Forest with Ensemble Approach | 96 | 96 | 96 | 96 |
| Decision Tree | 88 | 88 | 88 | 88 |
| KNN | 84 | 83 | 82 | 82.5 |
| Logistic Regression | 81 | 80 | 79 | 79.5 |

The above comparison shows the best model which can be used for non-invasive real-time malnutrition detection. The system uses Random Forest Ensemble because the comparison shows that the random forest is most suitable for different data sets and its prediction is strong. The result also shows that the random forest is the most suitable model to use because it remains the same for different data sets. The result of the system is strong, and it is good to use for real situations, especially in health care because when life is at stake even one failure is a big failure.

## V. METHODOLOGY

Different machine learning models were tried out, with the use of non-invasive sensors which are accurate and reliable in predicting malnutrition. The comparison shows how each model will perform and which ones are more suitable for real healthcare. Among all the models, Random Forest Ensemble is the best because it is most accurate with an accuracy of 96 and it is clear while explaining. The most important thing is that the system not only predicts well but also it explains the process of how it predicts it. This is very important for the user as well as healthcare workers.

The most understandable is Decision Tree but it is not accurate and it over fits which may lead to unstable behavior in real situation. Easy to use, Logistic Regression is accurate when the data is simple like straight line pattern but when the data is complex like real health data there is no straight-line pattern, so it fails to work. The above comparison shows the best model which can be used for non-invasive real-time malnutrition detection. The system uses Random Forest Ensemble because the comparison shows that the random forest is most suitable for different data sets and its prediction is strong. The result also shows that the random forest is the most suitable model to use because it remains the same for different data sets. The result of the system is strong, and it is good to use for real situations, especially in health care because when life is at stake even one failure is a big failure.

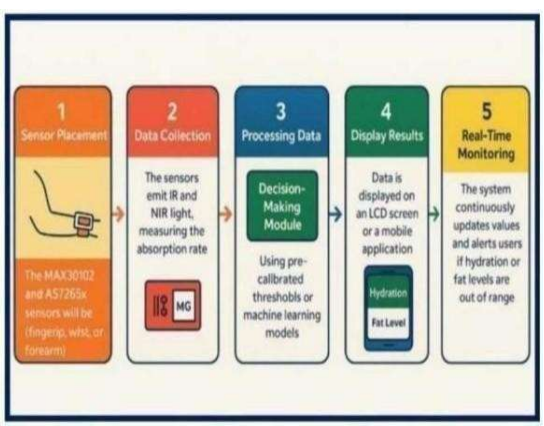



Fig. 1. Methodology Diagram

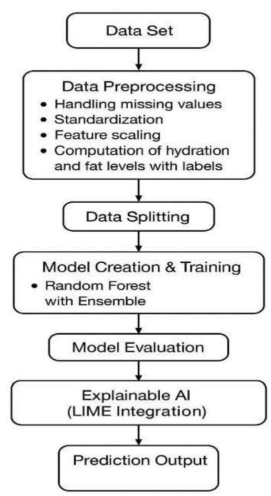



Fig. 2. Methodology Flow Chart

*A. Data Sets*

The data that was used for the prediction of malnutrition contains different health values such as the hydration level or the body fat percentage. These values are collected with non-invasive NIR sensors, namely MAX30102 or AS7265x.

A very powerful data cleaning was performed on the data. There were errors that had to be fixed, values that had to be filled, all measurements had to be converted into the same unit, etc. Finally, the data was segmented into the three nutrition classes Healthy, Undernourished and Obese by comparing the limits of body fat and hydration to create a nice and clean dataset which can be used nicely for the training and testing of the model.

*B. Data Loading and Processing*

The first step of data processing is the import of the dataset, which is formed by hydration and body fat percentage. The values are normalized so all the features stay in range. We fill the missing values in limits set so as not to leave the dataset polluted. We find the outliers, and we correct them so as not to affect the model.

After that we split the data into training and a test set to have proper learning and test set of the model. We do the feature scaling to keep the input values in a similar range so as not to slow down the learning of the model. This clean and organized way of processing the data keeps the input in a good range for the model and helps in the proper prediction of malnutrition.

*C. Data Sets*

The data that was used for the prediction of malnutrition contains different health values such as the hydration level or the body fat percentage. These values are collected with non-invasive NIR sensors, namely MAX30102 or AS7265x.

A very powerful data cleaning was performed on the data. There were errors that had to be fixed, values that had to be filled, all measurements had to be converted into the same unit, etc. Finally, the data was segmented into the three nutrition classes Healthy, Undernourished and Obese by comparing the limits of body fat and hydration to create a nice and clean dataset which can be used nicely for the training and testing of the model.

*D. Data Loading and Processing*

The first step of data processing is the import of the dataset, which is formed by hydration and body fat percentage. The values are normalized so all the features stay in range. We fill the missing values in limits set so as not to leave the dataset polluted. We find the outliers, and we correct them so as not to affect the model.

After that we split the data into training and a test set to have proper learning and test set of the model. We do the feature scaling to keep the input values in a similar range so as not to slow down the learning of the model. This clean and organized way of processing the data keeps the input in a good range for the model and helps in the proper prediction of malnutrition.

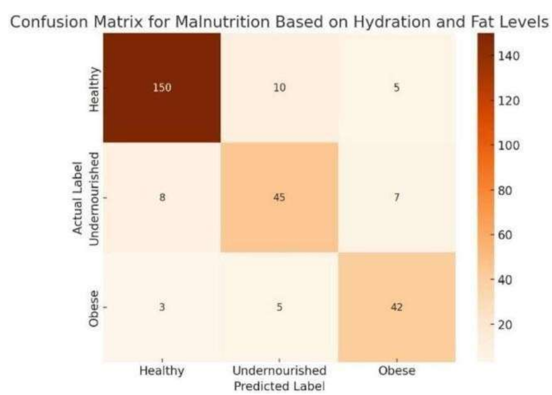



Fig. 3. Confusion Matrix for Malnutrition

*E. Model Creation*

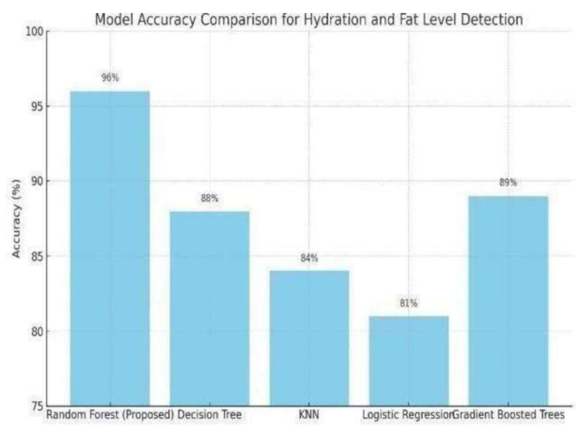
Machine learning models for predicting malnutrition by classifying the nutrition level based on hydration and body fat percentage is built. Then try all models-Random Forest, Decision Tree, KNN, and Logistic Regression to see which of these will produce the best result. Finally, choose Random Forest with ensemble method because it gets the highest accuracy ~ 96%.

*F. Model Evolution*

The output classes contain nutritional states: Healthy, Undernourished, Obese- including all the true and false positive/negatives displayed in a confusion matrix. The feature importance analysis demonstrates the effect of hydration level and body fat percentage on the output and creates some more explainability in the model. These forms of evaluation together help to confirm the effectiveness of the model and where improvements can be made.

*G. Model Accuracy Comparison*

Bar chart illustrates the accuracy of models to detect label hydration and fat levels. Highest accuracy (96%) is achieved by Random Forest proposed model. Following that is Gradient Boosted Trees with accuracy of 89%. Rest of the accuracies are relatively lower with Decision Tree at 88%, KNN at 84% and Logistic Regression at 81%. Hence Random Forest is the most reliable model to predict malnutrition.




4782

THE PUJITHA HOSPITAL

Accident ■ Maternity ■ Multi Speciality

PATIENT NAME : D.NAMRUTHA 20Y /F 25/02/2025

REF BY DOCTOR : Dr. VASU KARLAPUDI M.S (Ortho)

**Nutritional Health Report**

| INVESTIGATION | RESULT | UNITS | NORMAL RANG |
|---|---|---|---|
| Carbohydrates | 43% | % of Total Calories | 45-65% of total calories |
| Proteins | 20% | % of Total Calories | 10-35% of total calories |
| Fats | 27% | % of Total Calories | 20-35% of total calories |
| Water | 62% | Percentage (%) | 45-70% of body weight |

***END OF THE REPORT***

LAB INCHARGE

Fig. 4. Comparisons of accuracies of various models

Fig. 5. Validation

They compared the results of the model with the actual medical reports of Pujitha hospital for hydration and fat levels, and the results were nearly the same as clinical measurements. This indicates that the model is very accurate and can be trusted to detect malnutrition. This shows that the model works in real-time health and gives early nutritional help.

## VI. RESULT

Hardware design employed the MAX30102 and AS726x NIR sensors in combination, which offered real- time and non- invasive fat and hydration level measurements.

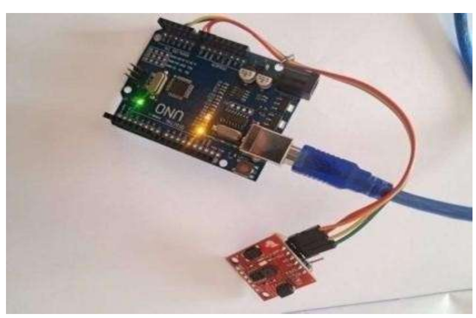



Fig. 6 Arduino Uno with NIRSensor

These sensors measure the composition of the tissue by placing it on the skin and checking how the skin absorbs the near- infrared light. These sensor values are read by the Arduino Uno microcontroller, which further processes it and displays it on the LCD screen. It can also transmit the data to mobile apps like Blank or to cloud services like thing speak.

Easy to wear, carry and use; it will be useful in places where other tests are not available regularly, i.e. in remote or rural areas. The feature of tracking it in real-time and giving alerts in case of any irregularity is also very useful in preventive healthcare.

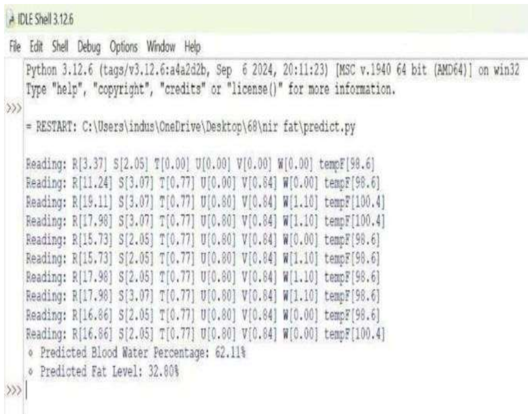



Fig. 7 Data Observed for Hydration and Fat Level

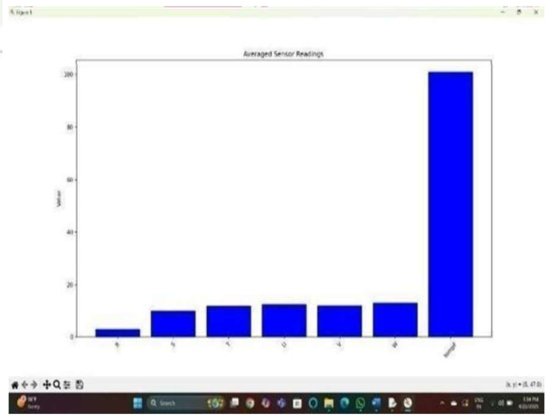



Fig. 8 Averaged Sensor Readings

Sensor data and prediction results are made available in visual interfaces, as evident in Figures 5.2 and 5.3. Visualizations in this work include real-time sensor data and time-moving averages, as well as hydration and body fat percentage results. Timestamped data logs allow trending and facilitate longitudinal monitoring of a person's nutritional status. Visualization not only aids interpretability by healthcare professionals but also increases user engagement since health information is made more salient and comprehensible.

## VII. Conclusion

When AI meets NIR sensors: The system detects malnutrition quickly, noninvasively, and very accurately. With an accuracy of 96%, the Random Forest method augmented with ensemble methods proves effective at predicting malnutrition using hydration and fat indicators. Despite all that, these methods remain expensive, limited in scalability, and deficient in micronutrient detection. The authors recommend that, in the future, efforts should be directed toward reducing cost, improving sensor accuracy, and developing better AI methods to turn this technology into a scalable and potent weapon against malnutrition.

## References


[1] National Family Health Survey (NFHS-4), National Family Health Survey India, 2015–16. Ministry of Health and Family Welfare, Government of India, 2016. [Online]. Available: https://rchiips.org/nfhs/NFHS-4Reports/India.pdf

[2] BMJ Public Health, Challenges in Implementation of Nutritional Programs in India, 2023. [Online]. Available: https://www.bmjpublichealth.org/challenges-nutrition-programs-india

[3] UNICEF South Asia, South Asia Nutrition Report, 2024. [Online]. Available: https://www.unicef.org/rosa/reports/south-asia- nutrition-report-2024

[4] UNICEF Data, Child Health and Diarrheal Disease, 2023. [Online]. Available: https://data.unicef.org/topic/child-health/diarrhoeal-disease

[5] UNICEF South Asia, Nutrition Policies for Women and Children, 2024. [Online]. Available: https://www.unicef.org/rosa/reports/nutrition-policies-women-children-2024

[6] Arnold, Early Malnutrition and Infant Mortality: Insights from UC Berkeley and UC San Francisco Research, 2022. [Online]. Available: https://www.nature.com/articles

[7] UNICEF, The State of the World's Children: Nutrition Report, 2022. [Online]. Available: https://data.unicef.org/topic/nutrition/malnutrition

[8] World Health Organization (WHO), Malnutrition Fact Sheet, 2021. [Online]. Available: https://www.who.int/factsheets/detail/malnutrition

[9] Food and Agriculture Organization (FAO), The Global Report on Food Crises, 2022.[Online]. Available: https://www.fao.org/global-report/en

[10] J. Smith et al., "Seasonal Patterns of Wasting and Stunting in South Asia," WHO Report, 2021. [Online]. Available: https://www.who.int/publications/item/9789240019700

[11] A. Mertens, Breaking the Cycle of Malnutrition through Early Interventions, UC Berkeley Research, 2022. [Online]. Available: https://www.ucberkeley.edu/research/malnutrition-interventions