JPPIPA 9(Special Issue) (2023)

Journal of Science Education Research

Journal of Research in Science Education

http://jppipa.unram.ac.id/index.php/jppipa/index

Development Edge Device Monitoring System Stunting and Malnutrition in Golden age 0–5 years Integrated with AI

Nurdina widanti[1*], Wike Handini[1], Nur Witdi Yanto[1], Aditya Alamsyah[1]

[1] Universitas Jayabaya, Electrical Engineering, East Jakarta, Indonesia

Received: October 17, 2023
Revised: November 25, 2023
Accepted: December 25, 2023
Published: December 31, 2023

Corresponding Author:
Nurdina Widanti
dina.dinawidi.widi7@gmail.com

DOI: 10.29303/jppipa.v9iSpecialIssue.6397

Abstract: Golden age is the best period for a child's growth, monitoring of growth and development must be carried out regularly. Growth and development disorders in children are stunting and malnutrition. This incident also prompted the government through the Ministry of Health to create a special program towards a golden Indonesia 2045 to monitor stunting and disease, especially in children. The prevalence of stunting decreased to 21.6% from 24.4% in 2022. Early detection of stunting and malnutrition, where the research object is children aged 0-5 years. This prototype was built using a load cell sensor, a study of the use of optical sensors and ultrasonic sensors to measure body height, and a MAX sensor to detect children's anemia. The integration of this tool combines IoT and AI. The results obtained to validate the use of load cells have a reading error of 0.01% with an accuracy of 99%. Comparison using optical sensors and ultrasonic sensors. Optical sensors have result average error of 0.01, accuracy 98.99%, ultrasonic sensors error was 0. 15 with 85% accuracy. To measure malnutrition, the anemia parameters were processed using the Dense Neural Network (DNN) model with 256 neurons showing an accuracy of 98.03%.

Keywords: Edge Devices; Golde Age; Machine Learning; Malnutrition; Stunting.

Introduction

To support the government's program towards the golden generation of 2045, one of them is to overcome the problems of malnutrition and stunting. Health indicators in society are monitoring nutrition, immunization and child growth (kemenkes RI, 2010). Imbalance of nutrition in the body triggers stunting, and results in disruption of body functions and becomes very dangerous if this is not monitored properly. Parental knowledge, environment and economic level really support the fulfillment of nutrition during the golden period of children's growth and development in the first 1000 days. Children need adequate nutritional intake to optimize their growth.

Data from the World Bank states that the workforce that experienced stunting in their infancy reached 54%. This means that 54% of the current workforce are stunting survivors. This is what makes stunting a serious concern for the government (BKKBN, 2022). And it is reported that in 2022, the prevalence of stunting in Indonesia will begin to decline to 21.6% from 24.4% (kemenkes RI, 2023), shown in Figure 1, the distribution of stunting in Indonesia (Fundrika, 2022).

Sustainable Development Goals (SDGs) in the health sector state that there will be no more incidents of malnutrition, in accordance with the 2025 international target of reducing the incidence of stunting and wasting, providing good nutritional balance for pregnant and breastfeeding women, children and teenagers (Unicef, 2022). Stunting is short height, it can even be very short if seen based on height compared to age (H/A) with a z-score value between -3 SD to <-2 SD in children under 5 years (WHO, 2020)(humas bkpk, n.d.). There are 4 ways

How to Cite:
Widanti, N., Handini, W., Yanto, N.W., & Alamsyah, A. (2023). Development Edge Device Monitoring System Stunting and Malnutrition in Golden age 0–5 years Integrated with AI. *Jurnal Penelitian Pendidikan IPA*, *9*(SpecialIssue), 247–253. https://doi.org/10.29303/jppipa.v9iSpecialIssue.6397

to solve the problem in this case, namely (P2PTM Kemenkes RI, 2018):

1. Provide exclusive breastfeeding to babies up to 6 months old;
2. Monitor children's development and take them to posyandu regularly;
3. Regularly consume Blood Supplement Tablets (BST);
4. Provide MPASI which is nutritious and rich in animal protein for babies over 6 months old.

Figure 1. Stunting Distribution(Fundrika, 2022)

Nutritional status (H/A) and adequate levels of energy, protein and iron are significantly related to children's gross motor development (Anggorowati, 2013), malnutrition is closely related to child development. Nutritional status (H/A) and adequate levels of energy, protein and iron are significantly related to children's gross motor development (Clark, 208 C.E.). From this background, an innovative tool was created to record height and weight as a parameter for stunting and hemoglobin levels to prevent animea as a parameter for malnutrition in children which were integrated into one edge device.

Previous research has been carried out to detect stunting and anemia, but combining both parameters and presenting them in one interactive application is not yet available. Several methods have been used to detect animea, one of which is the POCT method (Nidianti et al., 2019), then there is also testing using premier data which is carried out at posyandu (Nurlita et al., 2021) as well as several studies using stunting detection methods with AI (Roni et al., 2022), IoT (Rafaleony Berlian Putri Widodo, 2022), for animea detection (Ningsih et al., 2019)(REZZA, nd), development of a stunting detection application (Zenit Rohmaningrum, 2021), so far the algorithm still uses machine learning for animea detection using the SVM, ANN, DT, KNN method (Bitew et al., 2022)(Krishna Kishore et al., 2023)(Md. Merajul Islam af, Md. Jahanur Rahman a, Md Moidul Islam a, Dulal Chandra Roy a, NAM Faisal Ahmed b, Sadiq Hussain c, Md Amanullah d, Md. Menhazul Abedin e, 2022)(Children & New, 2023)(Fenta et al., 2021)(Jahidur Rahman Khan, Jabed H., 201 CE).

Technology built using edge devices by integrating IoT (Internet of Things) and Dense Neural Network (DNN) to process animea data into a model that is ready to use. The sensors used include MAX sensors, load cells, optical sensors. Equipped with a web-based application that can be accessed anytime and anywhere without having to install an application along with system reminders. And parents can monitor children's nutritional levels, indications of stunting and malnutrition in one system.

Method

System Hardware Design

To research indications of stunting and malnutrition in children aged 0-5 years, this was carried out at the posyandu in collaboration with PKK RW 12 Karanggan Bogor mothers. To build this system there are several steps, namely hardware design and user interface design.

The hardware design for the stunting detection system was made using a load cell sensor to measure body weight, comparing the performance of the VL53LO sensor with ultrasonic to get the best value, and also the MAX 30100 sensor to detect animea levels, in Figure 2 shows the system created, Figure 3 is Realization of hardware for children aged 0-1 year, and for Figure 4 is hardware for children aged 2-5 years.

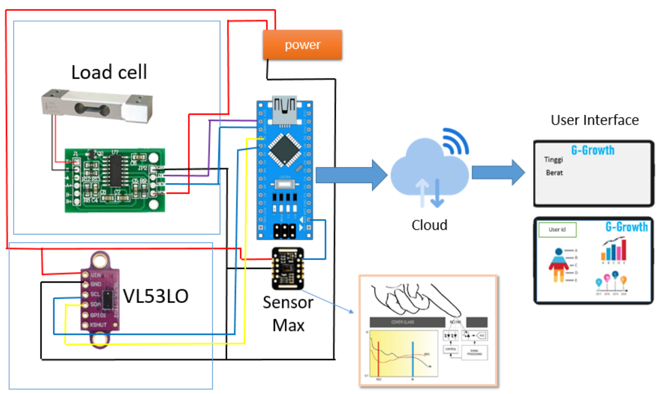

Figure 2. hardware design system

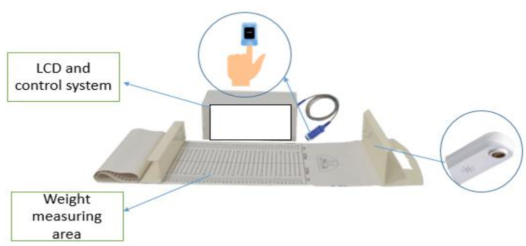

Figure 3. Hardware realization for children aged 0-1 year

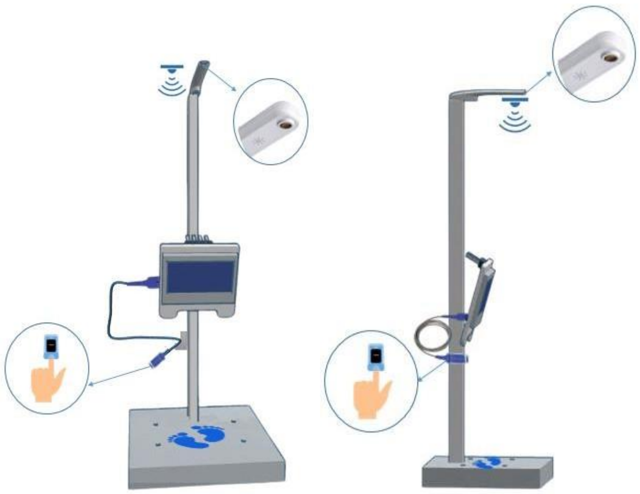

Figure 4. Hardware for children aged 2-5 years

User Interface Design

The data taken by the sensors will be sent directly to the cloud server where the data will then be processed and displayed on web.

Dataset Creation

The stages of creating the machine learning model that will be used in this research, where the machine learning model uses the Python programming language with the DNN model, is targeted for the model to reach R2 > 0.92. Table 1 provides the formation of the animea dataset.

Standardization of measurements

To determine whether a child is stunted and has good nutrition or not (Ministry of Health, 2020) shown in Table 2.

Table 1. Animea Dataset

Ed	IR	Hb
76438.7	85542.1	8.20
76463.9	85572.8	8.20
76677.0	85712.2	8.20
76684.8	85817.6	8.20
76686.9	85899.2	8.20
77178.1	86241.3	8.20
77431.4	86387.2	8.20
77452.9	86430.0	8.20
77746.7	86695.4	8.20
78362.9	87139.7	8.20
78396.8	87206.2	8.20
78433.1	87264.7	8.20
77222.2	80678.7	11.9
77249.3	80749.4	11.9
77301.5	80789.8	11.9
77319.1	80829.4	11.9
77336.4	80863.0	11.9
77345.6	80882.5	11.9
77355.7	80907.3	11.9
73726.0	82385.2	10.8
73761.9	82404.9	10.8
73876.2	82447.5	10.8
73891.0	82468.5	10.8
73906.7	82531.4	10.8
73997.8	82544.3	10.8
74079.8	82596.1	10.8
74145.0	82601.1	10.8
74154.4	82636.6	10.8
74380.5	82666.1	10.8
74415.6	82726.5	10.8
71216.5	82826.0	15.8
71495.0	82952.2	15.8
71513.7	83092.6	15.8
71543.5	83120.4	15.8
71560.0	83129.0	15.8
71840.2	83368.6	15.8
71867.2	83386.0	15.8
71958.1	83386.6	15.8
71969.2	83390.0	15.8

Table 2. Standardization of Measurements

Index	Nutritional Status Category	Threshold (Z-Score)
Weight by Age (W/A) children aged 0-60 months	Severely underweight	<-3 SD
	Underweight	-3 SD to <-2 SD
	Normal	-2 SD to +1 SD
	Risk of being overweight	> +1 SD
Body Length or Height by Age (BL/A or H/A) children aged 0-60 months	Severely stunted	<-3 SD
	Stunted	-3 SD to <-2 SD
	Normal	-2 SD to +3 SD
	High	> +3 SD
Weight by Body Length or Height (W/BL or W/H) children aged 0-60 months	Severely wasted	<-3 SD
	Wasted	-3 SD to <-2 SD
	Normal	-2 SD to +1 SD
	Possible risk of overweight	> +1 SD to +2 SD
	Overweight	> +2 SD to +3 SD
	Obese	> +3 SD
Body Mass Index by Age (BMI/A) children aged 0-60 months	Severely wasted	<-3 SD
	Wasted	-3 SD to <-2 SD
	Normal	-2 SD to +1 SD
	Possible risk of overweight	> +1 SD to +2 SD
	Overweight	> +2 SD to +3 SD
	Obese	> +3 SD
Body Mass Index by Age (BMI/A) children aged 5-18 years	Severely thinnes	<-3 SD
	Thinner	-3 SD to <-2 SD
	Normal	-2 SD to +1 SD
	Overweight	> +1 SD to +2 SD
	Obese	> +2 SD

Analysis

System evaluation is divided into 2, namely model evaluation for animea data processing and also sensor evaluation for weight and height reduction. For evaluation of weight and height measurements, data validation tests will be used with calibrated measuring instruments and the two values are compared to obtain error values and accuracy values.

$$eror = \frac{|aproximate - exact|}{exact}\ x\ 100\% \quad (1)$$

$$accuracy = 100\% - (\frac{|aproximate - exact|}{exact} x\ 100\%) \quad (2)$$

To evaluate AI using several methods. Evaluation of the model's algorithm performance in predicting is carried out using a loss function. The loss function determines the error distance between the algorithm's predicted results and the expected output. The method used is:

1. Mean Absolute Error (MAE)
   MAE or Mean Absolute Error shows the average error value which is the error between the actual value and the predicted value. MAE itself is generally used to measure prediction error in time series analysis. The formula for calculating MAE is:

   $$MAE = \sum \frac{|Y' - Y|}{n} \quad (3)$$

   Y' is the predicted value, Y is the true value and n is the amount of data.
2. Mean Squared Error (MSE)
   MSE measures the average value of the total squared difference between the model predicted value and the actual value(Bayangkari Karno, 2020) The formula for calculating MSE is:

   $$MSE = \sum \frac{|Y' - Y|^2}{n} \quad (4)$$

Results and Discussion

Testing is carried out to test sensor readings and also validate whether the readings are good enough or not, where the sensor data tested is max sensor data, load cell sensor and VL53LO optical and ultrasonic sensors. Important notes in storing tools and using tools must be in the range 0-40 with humidity 10-90% RH.°C.

Load Cell sensor test results

This test was carried out using a weighing pendulum which varied from 500 grams to 2kg with the results obtained as in Table 3. Sensor testing was carried out at a temperature of 36 °C.

Table 3. Weight Measurement Results

Weighing pendulum (Kg)	Load cell sensor (Kg)	Error (%)	Accuracy (%)
0.5	0.5	0.00	100
0.5	0.5	0.00	100
0.5	0.5	0.00	100
0.5	0.5	0.00	100
1	1	0.00	100
1	0.98	0.02	98
1.5	1.52	0.01	99
1.5	1.53	0.02	98
2	2	0.00	100
2	1.99	0.01	99
Average		0.01	99

From the test results on the sensor with 10 different data with a sampling interval every 1 minute, the average error result was 0.01 and the average measurement accuracy was 99%. From this data, it can be ensured that the load cell sensor readings are running well and had high accuracy.

Results of Testing the Effectiveness of the VL35LO Sensor with an Ultrasonic Sensor

This test aims to compare the optimization of Height measurements, as shown in Tables 4 and 5 respectively. From the test results on both sensors with varying distance ranges from 10 cm to 100 cm, the results were obtained that using the VL53LO sensor had better reading and was still very optimal up to a distance of 100 cm, but for the Ultrasonic sensor, even though we bought it with sensor specifications, it could measure up to 2 meters. The furthest distance was proven in measurements when the distance was 75 cm. The reading started to have an error of 0.31 and the sensor accuracy was only 65%. This is not good for the tool being built because this prototype requires a high level of accuracy, so the VL53LO sensor is considered good enough to support height measurements with high sensor accuracy of 98.99%.

Table 4. Testing with the VL350 optical sensor.

Height (cm)	VL53LO (cm)	Error (%)	Accuracy (%)
10	9.8	0.02	98.00
25	25.1	0.00	99.60
50	50.1	0.00	99.80
75	74	0.01	98.67
100	98.9	0.01	98.90
Average		0.01	98.99

Table 5. Testing with ultrasonic sensors

Height (cm)	Ultrasonic sensor (cm)	Error (%)	Accuracy (%)
10	10	0.00	100
25	25.6	0.02	98
50	49.8	0.00	100
75	52	0.31	69
100	60	0.40	60
Average		0.15	85

Testing training data results for the max30100 sensor

This test was carried out using coding directly on the system and obtained results as in Table 6.

Table 6. Training data results

		MAE		
Neurons	Losses	Val_Loss	R2	Val_R2
128	14.764	13.207	0.2954	0.372
128	0.6503	0.7121	0.7987	0.7189
128	0.4835	0.5641	0.8680	0.7613
256	0.4987	0.5450	0.8712	0.803
		MSE		
Neurons	Losses	Val_Loss	R2	Val_R2
128	2.109	25.910	0.5732	0.4201
128	10.783	13.459	0.7885	0.689
128	0.5795	0.7577	0.8875	0.823
256	0.3699	0.6247	0.9232	0.8612

From the results of training, it can be seen that in MSE with 256 neurons the results shown are quite optimal and sufficient to be a model of the animea system, so that the model will use 256 neurons.

Testing Integrated System

After the entire system is installed and integrated with each other as in Figure 5, we tested the tool. Figure 6 shows the results of measuring stunting and nutritional status of children. Table 7 provide data for the reading results and precision of animea levels in children.

Figure 5. System integration

Figure 6. System reading results

Table 7. Animea sensor reading with Max 30100 sensor

HB with easy touch	Hb with Max30100	Error (%)	Accuracy (%)
11.9	11.6	0.03	97.48
11.8	12	0.02	98.31
12	11.8	0.02	98.33
12	11.5	0.04	95.83
11	11.2	0.02	98.18
11.5	11.6	0.01	99.13
12.9	13	0.01	99.22
13	13.8	0.06	93.85
11	11	0.00	100.00
10	10	0.00	100.00
Average		0.02	98.03

From the test results, an error result of 0.02 was obtained and the reading accuracy was 98.03%.

Conclusion

After carrying out all the stages, it was found that for testing the load cell sensor which is intended for measuring children's weight, an average sensor accuracy of 99% was obtained. For measuring body height, from the experimental results it was found that the use of the VL53L0 sensor was more optimal with an average sensor accuracy of 98%. When the system integrate has result for accuracy is 99%. quite good results were obtained where the results could be read on the system and could be displayed well and for the results of reading animea levels using DNN with 256 neurons, the results obtained an average accuracy in reading of 98.03%. From the users and also the companions who took part in the testing, it was said that the tool was easy to use because one direct measurement can directly measure 3 parameters and shorten the measurement time, especially if the child has a feeling of trauma or fear when taking measurements.

Acknowledgments

This research was funded by the Ministry of Education and Culture's BIMA Grant under the Beginner Lecturer Research scheme, with main contract number 179/E5/PG.02.00/PL/2023, and derivative contract numbers 1414/LL3/AL.04/2023, 2.2/PKH/LPPM-UJ /VII/2023

Author Contributions

Conceptualization, NW; methodology, NW, WH, and NWY; validation, NW; investigation, WH; resources, NW, WH, and NWY.; data curation, NW, WH, and NWY; writing–original draft preparation, NW, and WH; writing–review and editing, NW, and WH. All authors have read and agreed to the published version of the manuscript.

Funding

BIMA Ministry of Education and Culture grant with the Beginner Lecturer Research scheme, with main contract number 179/E5/PG.02.00/PL/2023, and derivative contract numbers 1414/LL3/AL.04/2023, 2.2/PKH/LPPM-UJ/VII/2023

Conflicts of Interest
The authors declare no conflict of interest

References

Anggorowati, L. (2013). Anemia Terhadap Pertumbuhan Dan Perkembangan Anak Malnutrisi. *Jurnal Kesehatan Masyarakat Andalas*, *11*(1), 87–95.

Bayangkari Karno, A. S. (2020). Analisis Data Time Series Menggunakan Lstm (Long Short Term Memory) Dan Arima (Autocorrelation Integrated Moving Average) Dalam Bahasa Python. *Ultima Infosys : Jurnal Ilmu Sistem Informasi*, *11*(1), 1–7. Https://Doi.Org/10.31937/Si.V9i1.1223

Bitew, F. H., Sparks, C. S., & Nyarko, S. H. (2022). Machine Learning Algorithms For Predicting Undernutrition Among Under-Five Children In Ethiopia. *Public Health Nutrition*, *25*(2), 269–280. Https://Doi.Org/10.1017/S1368980021004262

Bkkbn. (2022). *Angka Stunting*. Https://Www.Bkkbn.Go.Id/Berita-Indonesia-Cegah-Stunting

Children, U., & New, P. (2023). *Machine Learning Algorithms For Predicting Stunting Among Under-Five Children In Papua New Guinea*.

Clark, S. (208 C.E.). *Iron Deficiency Anemia. Nutrition In Clinical Practice,*.

Fenta, H. M., Zewotir, T., & Muluneh, E. K. (2021). A Machine Learning Classifier Approach For Identifying The Determinants Of Under-Five Child Undernutrition In Ethiopian Administrative Zones. *Bmc Medical Informatics And Decision Making*, *21*(1), 1–12. Https://Doi.Org/10.1186/S12911-021-01652-1

Fundrika, B. A. (2022). Menuju Indonesia Bebas Stunting, Bisakah Gerakan Makan Telur Dan Ikan Setiap Hari Jadi Solusi? In *Suara.Com*. Https://Www.Suara.Com/Health/2022/09/09/070500/Indonesia-Targetkan-Prevalensi-Stunting-14-Persen-Di-2024-Bisakah-Gerakan-Makan-Telur-Setiap-Hari-Jadi-Solusi

Humas Bkpk. (N.D.). *Dua Titik Penting Intervensi Stunting - Badan Kebijakan Pembangunan Kesehatan _ Bkpk Kemenkes*.

Jahidur Rahman Khan, Jabed H., J. H. T. (201 C.E.). A Machine Learning Classifier Approach For Identifying The Determinants Of Under-Five Child Undernutrition In Ethiopian Administrative Zones. *Informatics For Health And Social Care*, *46*(4), 425–442.

Kemenkes Ri. (2010). *24 Indikator Kesehatan Dalam Ipkm – Sehat Negeriku*. Https://Sehatnegeriku.Kemkes.Go.Id/Baca/Rilis-Media/20101210/37636/24-Indikator-Kesehatan-Dalam-Ipkm/

Kemenkes Ri. (2023). Prevalensi Stunting Di Indonesia Turun Ke 21,6% Dari 24,4%. In *25 Januari 2023* (P. 1). Https://Sehatnegeriku.Kemkes.Go.Id/Baca/Rilis-Media/20230125/3142280/Prevalensi-Stunting-Di-Indonesia-Turun-Ke-216-Dari-244/#:~:Text=Standard Who Terkait Prevalensi Stunting,Usia 6 Sampai 2 Tahun.

Kementrian Kesehatan. (2020). *Peraturan Menteri Kesehatan Republik Indonesia Nomor 2 Tahun 2020 Tentang Standar Antropometri Anak*.

Krishna Kishore, K., Venkata Suman, J., Lakshmi Mnikyamba, I., Rao Polamuri, S., & Kishore Koagnti, K. (2023). *Prediction Of Malnutrition In New Born Infants Using Machine Learning Techniques Prediction Of Malnutrition In Newborn Infants Using Machine Learning Techniques*. Https://Doi.Org/10.21203/Rs.3.Rs-2958834/V1

Md. Merajul Islam A F, Md. Jahanur Rahman A, Md Moidul Islam A, Dulal Chandra Roy A, N.A.M. Faisal Ahmed B, Sadiq Hussain C, Md Amanullah D, Md. Menhazul Abedin E, M. M. E. (2022). Application Of Machine Learning Based Algorithm For Prediction Of Malnutrition Among Women In Bangladesh. *International Journal Of Cognitive Computing In Engineering*, *3*, 46–57. Https://Doi.Org/International Journal Of Cognitive Computing In Engineering

Nidianti, E., Nugraha, G., Aulia, I. A. N., Syadzila, S. K., Suciati, S. S., & Utami, N. D. (2019). Pemeriksaan Kadar Hemoglobin Dengan Metode Poct (Point Of Care Testing) Sebagai Deteksi Dini Penyakit Anemia Bagi Masyarakat Desa Sumbersono, Mojokerto. *Jurnal Surya Masyarakat*, *2*(1), 29. Https://Doi.Org/10.26714/Jsm.2.1.2019.29-34

Ningsih, E. W., Fajrin, H. R., & Fitriyah, A. (2019). Pendeteksi Hemoglobin Non Invasive. *Medika Teknika : Jurnal Teknik Elektromedik Indonesia*, *1*(1). Https://Doi.Org/10.18196/Mt.010102

Nurlita, A. N., Wigati, M., Hasanbasri, M., Jumarko, J., & Helmyati, S. (2021). Development Of Stunting Early Detection Kit For Children Under Two Years: Validity And Reliability. *Jurnal Gizi Dan Pangan*, *16*(1), 39–46. Https://Doi.Org/10.25182/Jgp.2021.16.1.39-46

P2ptm Kemenkes Ri. (2018). Cegah Stunting Dengan Perbaikan Pola Makan, Pola Asuh Dan Sanitasi - Direktorat P2ptm. In *Kemkes.Go.Id*. Http://P2ptm.Kemkes.Go.Id/Kegiatan-P2ptm/Subdit-Penyakit-Diabetes-Melitus-Dan-Gangguan-Metabolik/Cegah-Stunting-Dengan-Perbaikan-Pola-Makan-Pola-Asuh-Dan-Sanitasi

Rafaleony Berlian Putri Widodo, Dkk. (2022). E-Stare

(Electronic Stunting Care): Inovasi Aplikasi Pencegah Stunting Sebagai Upaya Preventif Dan Promotif Berbasis Iot (Internet Of Things) Untuk Mencapai Indonesia Bebas Stunting. In *Indonesian Student Competition (Insco-1) Asosiasi Institusi Pendidikan Ners Indonesia (Aipni)* (Vol. 33, Issue 1, Pp. 1–12).

Rezza, M. (N.D.). *Perancangan Dan Implementasi Alat Ukur Kadar Hemoglobin Darah Secara Non-Invasive Berbasis Arduino*.

Roni, M., Syauqy, D., & Primananda, R. (2022). *Rancang Bangun Sistem Deteksi Dini Status Gizi Dan Risiko Stunting Pada Balita Berdasarkan Tinggi Dan Berat Badan Menggunakan Metode Jst Backpropagation*. *6*(7), 3155–3160. Http://J-Ptiik.Ub.Ac.Id

Unicef. (2022). Malnutrition In Children - Unicef Data. In *Unicef*. Https://Data.Unicef.Org/Topic/Nutrition/Malnutrition/

Who. (2020). Stunting Prevalence Among Children Under 5 Years Of Age (%) (Model-Based Estimates). In *Global Health Observatory Data Repository* (P. 35). Https://Www.Who.Int/Data/Gho/Data/Indicators/Indicator-Details/Gho/Gho-Jme-Stunting-Prevalence

Zenit Rohmaningrum, D. (2021). *Pengembangan Aplikasi "Anc.Mia Care" Sebagai Upaya Deteksi Dini Dan Pencegahan Anemia Pada Ibu Hamil Dalam Rangka Mewujudkan Indonesia Bebas Stunting* (Issue 22020120120008, Pp. 2013–2015).