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Implementation of Machine Learning in Determining Nutritional Status using the Complete Linkage Agglomerative Hierarchical Clustering Method

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ABSTRACT

Problems that often occur in the nutritional status of children can be done prevention in the form of input to the people of north Aceh on the importance of fulfilling nutrition in toddlers in order to avoid stunting. Lack of nutrition is one of the causes of problems experienced by toddlers in north Aceh. The role of local governments, hospitals and health services is needed in looking at the amount of nutritional status of children, especially areas in northern Aceh. This research aims to be able to determine the nutritional status of toddlers and can provide convenience for hospital officials and doctors in handling gradually and how to treat on a scale in diagnosing diseases with child nutritional status. The first method of this study is to group toddlers identified nutritional status of children who are classified as stunting or not and then grouped areas that are malnourished children using hierarchical agglomerative models. The results of this study can diagnose nutritional status in children with Machine Learning using complete linkage agglomerative hierarchical clustering whose final results can see areas prone to stunting. The data to be modeled consists of 12 sub-districts with samples taken in the form of the number of cases of baktiya 12, dewantara 21, kuta makmur 83, meurah mulia 84, jambo aye 87, nibong 83, sacred store 68. the process of complete linkage agglomerative hierarchical clustering Baktiya method from Scaling Data (standardization)-1.344354111, Kuta Makmur1.376783706, Meurah Mulia 1.415109591, Cot Girek -0.462858762, Simpang Kramat0.801895435, Nisam Antara0.648591896. Based on the results of distance calculations, Prosedure was carried out up to 11 times resulting in cluster groups of 3,21,7,14.15 with a result of 0, clusters 17,23,8,13,18,20,11 with results of 1.6628305 and 1.4,10,19,26,2,9,5,12 with a value of 2.720995. The final calculation of 19,26,1,4,10 is 2.11633.

1. Introduction

The role of hospitals and health services is needed in looking at the amount of malnutrition in toddlers, especially in North Aceh to avoid lack of nutritional intake in children. Stunting is a nutritional imbalance that has an impact on decreasing the baby's growth speed. With population density it is very fast to get into the question of malnutrition [1]. This should be dealt with quickly. For now the handling of stunting must include all elements from various stakeholders [2].

Another problem is in nutrition related to health in the community. Other factors are the cause of nutritional problems including multifactorial. Therefore how to handle it should include all elements in the entire related sector [3]. The value of the last 3-4 years of undersized toddlers increased in 2016 by 26.5% to 27.6% in 2017. This is due to undernutrition, thinness, and fat [4]. Therefore, all health ministers and all agencies explain the importance of health knowledge in infants [5] [6] . Nutritional status can be seen from the

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balance between income and consumption that is consumed every day based on the categories inputted. Furthermore, in determining the important nutritional status of the classification of nutritional status and has a reference value based on the assessment that has been set [7].

Factors that affect the impact of stunting are mostly the role of women (mothers of stunting toddlers) who are not educated or low and lack informal knowledge only about 35.4% and 15.4% care about education, while 35.6% have mostly completed education well at a higher level of science [8]. In use for the determination of nutritional status of these variables are age, weight and height [9]. Then children under five who experience stunting growth, certainly have a low birth weight (BLBR) at the age of 6-24 months [10].

Medical record data on its management is implemented clustering that is included in Supervised Learning (an approach where there is already trained data, and there are targeted variables so that the purpose of this approach is to group a data into existing data [11] .

For toddlers who are stunting there is a problem of malnutrition and must be quick handlers. The most important thing is the presence of the toddler in posyandu and knowing quickly the factors that cause the toddler stunting that can be seen from the size of the baby's weight [12] .

2. Method

The research stages of Machine Learning Implementation on Determining Nutritional Status using the Complete Linkage Agglomerative Hierarchical Clustering method are the collection of data between sub-districts for the determination of Toddler Nutrition Status, disbursement of literature studies on the diagnosis of child nutrition and data to be included in complete linkage agglomerative hierarchical clustering, the existence of knowledge discovery in database (KDD) stages, determining the level of similarity between the two cases. so that at the end there is a calculation process where a process uses the K-Means Clustering Method, child data for the stage entered into the system, prepocessing stage, weighting stage, and looking for nila manhattan distance, the next process is to look at the value of agglomerative hierrchical clustering, view the silhoette coefficient process, then determine the results of the cluster with the agglomerative clustering procedure stage where each data is grouped with other data that has the closest distance. This procedure is done until it produces a cluster group.

3. Results and Analysis

3.1 Analysis of The System

Malnutrition is one of the problems experienced by toddlers in Indonesia. Readiness from the hospital and service is needed to reduce the nutritional status. The nutritional status in toddlers can be known by the value seen at the time of sampling. Then the Machine Learning Complete Linkage Agglomerative Hierarchical Clustering model can see areas in the nutritional status of toddlers poorly in toddlers, this study is one that can innovate with applied technology in the form of detecting the poor nutritional status of Complete Linkage Agglomerative Hierarchical Clustering.

3.2 Manual Calculation of Complete Linkage Agglomerative Hierarchical Clustering

a. Case Data

The following case data from The Determination of Nutritional Status using the Complete Linkage Agglomerative Hierarchical Clustering method are as follows:

Table 1.
Case Data

Number	District	Number of cases	Number	District	Number of cases
1	Baktiya	12	15	Sawang	78
2	Dewantara	21	16	Nisam	63
3	Kuta Makmur	83	17	Cot Girek	35
4	Lhoksukon	11	18	Langkahan	45
5	Matangkuli	27	19	Baktiya Barat	9
6	Muara Batu	66	20	Paya Bakong	46
7	Meurah Mulia	84	21	Nibong	83
8	Samudera	37	22	Simpang Kramat	68
9	Seunuddon	20	23	Lapang	34

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Number	District	Number of cases	Number	District	Number of cases
10	Syamtalira Aron	13	24	Pirak Timu	62
11	Syamtalira Bayu	49	25	Geurudong Pase	70
12	Tanah Luas	24	26	Banda Baro	6
13	Tanah Pasir	39	27	Nisam Antara	64
14	T. Jambo Aye	87			

b. Scaling Data (Standardization)

In the following the data scaling process is carried out to calculate the distance between the data, scaling with :

Table 2.
Scaling Data (Standardization)

No	District	Number of cases	Number	District	Number of cases
1	Baktiya	-1.344354111	15	Sawang	1.185154282
2	Dewantara	-0.999421148	16	Nisam	0.610266011
3	Kuta Makmur	1.376783706	17	Cot Girek	-0.462858762
4	Lhoksukon	-1.382679996	18	Langkahan	-0.079599914
5	Matangkuli	-0.76946584	19	Baktiya Barat	-1.459331765
6	Muara Batu	0.725243665	20	Paya Bakong	-0.04127403
7	Meurah Mulia	1.415109591	21	Nibong	1.376783706
8	Samudera	-0.386206992	22	Simpang Kramat	0.801895435
9	Seunuddon	-1.037747033	23	Lapang	-0.501184647
10	Syamtalira Aron	-1.306028226	24	Pirak Timu	0.571940126
11	Syamtalira Bayu	0.073703625	25	Geurudong Pase	0.878547204
12	Tanah Luas	-0.884443494	26	Banda Baro	-1.57430942
13	Tanah Pasir	-0.309555223	27	Nisam Antara	0.648591896
14	T. Jambo Aye	1.530087245			

c. Scaling Data (Standardization)

The following process of determining nutritional status using the complete linkage agglomerative hierarchical clustering method will be done next, the calculation of distance between data using eucludean distance, the data distance table is presented as follows::

Table 3
Eucludean distance

NO	1	2	3	…	…	…	25	26	27
1	0	0.340124	2.683204	0.037792	0.566874	2.040747	2.191913	0.22675	1.965163
2	0.340124	0	2.343079	0.377916	0.22675	1.700622	1.851789	0.566874	1.625039
3	2.683204	2.343079	0	2.720995	2.11633	0.642457	0.491291	2.909953	0.71804
.	..	..	..	..	..	..	..	..	..
.	..	..	..	..	..	..	..	..	..
25	2.191913	1.851789	0.491291	2.229705	1.625039	0.151166	0	2.418663	0.22675
26	0.22675	0.566874	2.909953	0.188958	0.793624	2.267496	2.418663	0	2.191913
27	1.965163	1.625039	0.71804	2.002955	1.398289	0.075583	0.22675	2.191913	0

d. End Group Result Data

Based on the results of distance calculations from determining nutritional status using the complete linkage agglomerative hierarchical clustering method, then the Agglomerative Hierarchical Clustering procedure is carried out for each data that will be grouped with other data by having the closest distance. The final result of this model method is to carry out the procedural process which is carried out up to 11 times so as to produce cluster groups as follows::

Table 4
Final Results of Agglomerative Hierarchical Clustering

NO	3,21,7,14,15	17,23,8,13,18,20,11	16,24,27,6,22,25	1,4,10,19,26,2,9,5,12
3,21,7,14,15	0	1.6628305	0.604666	2.720995
17,23,8,13,18,20,11	1.662831	0	1.058165	1.058165
16,24,27,6,22,25	0.604666	1.0581649	0	2.11633

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NO	3,21,7,14,15	17,23,8,13,18,20,11	16,24,27,6,22,25	1,4,10,19,26,2,9,5,12
19,26,1,4,10	2.720995	1.0581649	2.11633	0

3.3 System Implementation

a. Cluster Members

The following members of the machine learning implementation cluster on determining nutritional status using the complete linkage agglomerative hierarchical clustering method are as follows:

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	Kecamatan	JlKasus	cutree.hasil..k...4.
26	Banda Baro	6	1
3	Kuta Makmur	83	2
7	Meurah Mulia	84	2
14	T. Jambo Aye	87	2
15	Sawang	78	2
21	Nibong	83	2
6	Muara Batu	66	3
16	Nisam	63	3
22	Simpang Kramat	68	3
24	Pirak Timu	62	3
25	Geurudong Pase	70	3
27	Nisam Antara	64	3
8	Samudera	37	4
11	Syamtalira Bayu	49	4
13	Tanah Pasir	39	4
17	Cot Girek	35	4
18	Langkahan	45	4
20	Paya Bakong	46	4
23	Lapang	34	4

Fig 1. Cluster Members

b. Dendrogram cluster results

The following results of machine learning implementation on determining nutritional status using the complete linkage agglomerative hierarchical clustering method are as follows:

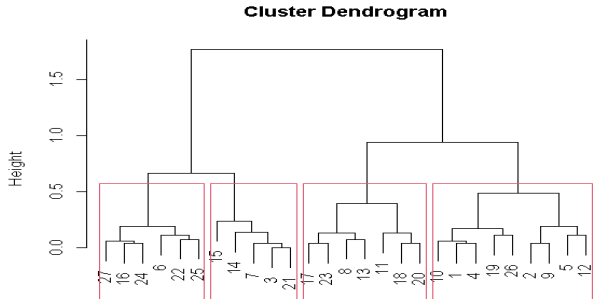

Fig 2. Dendrogram cluster results

4. Conclusion

a. Can know the process of grouping malnutrition under five in the application of machine learning model complete linkage agglomerative hierarchical clustering to see each cluster in each region.
b. The results of the complete linkage agglomerative hierarchical clustering model can be used in the policies of the health department and the hospital in considering the nutritional status of children in each region as a recommendation for the hospital.
c. the result of distance calculation, the Agglomerative Hierarchical Clustering procedure is performed, each data is grouped with other data which has the closest distance. This procedure was carried out up to 11 times so as to produce cluster groups of 3,21,7,14,15 with 17,23,8,13,18,20,11 values 1,0581649, the final stage 1,4,10,19,26,2, 9.5,12 with a value of 2.720995 and 19,26,1,4,10 with a value of 2.11633

5. References

[1] D. Aries, M., & Martianto, "Estimasi kerugian ekonomi akibat status gizi buruk dan biaya penanggulangannya pada balita di berbagai provinsi di Indonesia," J. Gizi dan Pangan, vol. 1(2), pp. 26–33, 2006.

[2] Kemenkes, "Hasil utama riset kesehatan dasar (Riskesdas) 2018. Kementrian kesehatan Republik Indonesia Badan Penelitian dan Pengembangan Kesehatan", 2018," 2018.
[3] I. F. Supariasa, B. Bakri, Penilaian status gizi. 2019.
[4] (2018) Dharmawan, Y. Zahraini, Atmarita, "Situasi Balita Pendek (stunting) di Indonesia", Data, P., & Informasi Kemenkes, R. I," J. Bul. Jendela Data dan Inf. Kesehat., no. Edisi I Tahun, pp. 1–13, 2018.
[5] E. Hartama, D., Mawengkang, H., Zarlis, M., Sembiring, R. W., Nasution, B. B., Syahruddin, M., ... & Irawan, "The Planning of Smart City to Mitigate the Impacts of Natural Disaster in North Sumatera," Int. Conf. Inf. Technol. Disaster Risk Reduct. Springer, Cham, pp. 147–154, 2016.
[6] K. Agung, K. Inna, "Overview of Stunting Prevalence of Toddlers and Related Factors in Indonesia: Advance Analysis of the Indonesian Health Profile 2017," 2017.
[7] N. D. Fahik, B., Djahi, B. S., & Rumlaklak, "Data Mining untuk Klasifikasi Status Gizi Desa di Kabupaten Malaka Menggunakan Metode K-nearest Neighbor," J. Komput. dan Inform., vol. 6(1), pp. 1–7, 2018.
[8] K. P. Kang, Y., Aguayo, V. M., Campbell, R. K., Dzed, L., Joshi, V., Waid, J. L., ... & West Jr, "Nutritional status and risk factors for stunting in preschool children in Bhutan. Maternal & child nutrition," Matern. Child Nutr., vol. 14, e12653, 2018.
[9] N. H. Putri, D. S. K., & Utami, "Nilai Batas Berat Lahir Sebagai Prediktor Kejadian Stunting Pada Anak Umur 6-23 Bulan Di Indonesia (Cut-Off Point Of Birthweight As Predictor Of Stunting In Children Aged 6-23 Months In Indonesia)," J. Penelit. Gizi dan Makanan, vol. 38(1), pp. 79–85, 2015.
[10] E. Nasution, D., Nurdiati, D. S., & Huriyati, "Berat badan lahir rendah (BBLR) dengan kejadian stunting pada anak usia 6-24 bulan," J. gizi Klin. Indones., no. 11(1), pp. 31–37.
[11] K. N. Brown, J. A., Carroll, J. D., Huddleston, B., Casias, Z., & Long, "A multiscale study of damage in elastomeric syntactic foams," J. Mater. Sci., no. 53(14), pp. 10479–10498, 2018.
[12] S. (2015) Destiadi, A., Nindya, T. S., & Sumarmi, "Frekuensi Kunjungan Posyandu dan Riwayat Kenaikan Berat Badan sebagai Faktor Risiko Kejadian Stunting pada Anak Usia 3–5 Tahun," Media Gizi Indones., vol. 10(1), pp. 71–75.
[13] I. F. Supariasa, B. Bakri, Penilaian status gizi. 2019.
[14] R. Ula, M., Hendriana, Y., & Hardi, "An expert system for early diagnose of vitamins and minerals deficiency on the body," Int. Conf. Inf. Technol. Syst. Innov., pp. 1–6, 2016.
[15] N. N. Nurfalinda, "Case Based Reasoning untuk Diagnosis Penyakit Gizi Buruk pada Balita," J. Sustain. J. Has. Penelit. dan Ind. Terap., vol. 53–60, 2017.
[16] M. Ula, M., Ulva, A. F., & Mauliza, "IMPLEMENTASI MACHINE LEARNING DENGAN MODEL CASE BASED REASONING DALAM MENDIAGNOSA GIZI BURUK PADA ANAK," J. Inform. Kaputama, no. 5(2), pp. 333–339.
[17] I. D. Yulianto, L. D., Triayudi, A., & Sholihati, "Implementation Educational Data Mining For Analysis of Student Performance Prediction with Comparison of K-Nearest Neighbor Data Mining Method and Decision Tree C4. 5: Implementation Educational Data Mining For Analysis of Student Performance Prediction w," J. Mantik, no. 4(1), pp. 441–451, 2020.
[18] A. Byna, Analisis Komparatif Machine Learning Untuk Klasifikasi Kejadian Stunting. Pena Persada, 2020.
[19] E. Sembiring, R.W., Zain, J.M., "Comparative Agglomerative Hierarchical Clustering Method to Cluster Implemented Course," J. Comput., vol. Vol 2, no. Issue 12, 2010.
[20] D. Patidar, G., Singh, A., & Singh, "An Approach for Document Clustering using Agglomerative Clustering and Hebbian-type Neural Network," Int. J. Comput. Appl., no. 75(9), 2013.
[21] H. A. K. Rosdiana, R., Ula, M., & Aidilof, "Implementasi Pemodelan Citra Model Svm (Support Vector Machine) Dalam Penentuan Pengklasifikasian Jenis Suara Kontes Burung," J. Inform. Kaputama, no. 5(2), pp. 317–324, 2021.

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