Journal of Dinda

Data Science, Information Technology, and Data Analytics

Vol. 4 No. 1 (2024) 14 - 22

E-ISSN: 2809-8064

Prediction of Obesity Classification Using K-Means Clustering

Aditya Wildan^{1*}, Helmy Akmal Burhansyah², Choki Ferdiansyah³

1,2,3*Software Engineering, Faculty of Informatics, Institut Teknologi Telkom Purwokerto 1*21104077@ittelkom-pwt.ac.id, 221104079@ittelkom-pwt.ac.id, 321104017@ittelkom-pwt.ac.id

Abstract

This paper aims to determine the difference between someone who is obese and who is not and classify the level of obesity by utilizing the K-Means clustering algorithm to group them. The move was taken as part of obesity prevention efforts, with the hope that a deeper understanding of the distribution of obesity within specific categories could help design more specific and effective interventions. Using this approach, it is hoped that this study can contribute to our understanding of the complexities of obesity and encourage more precise and targeted preventive measures. In this study we used datasets from Kaggle. It is used to classify the difference between underweight and overweight people. In this study, data was processed using Data Mining techniques with the K-Means method. Based on the classification, four clusters were categorized. Cluster 0 in this cluster only has women, with an age range ranging from 45 to 60 years. Relatively thin to normal weight. Cluster 1 only has men, with an age range of more than 40 years and 55 to 60 years. People in this cluster are overweight or obese. Cluster 2 women aged 15-70 years make up the majority in this group, with women aged 55-60 years as the highest proportion. In general, they have a normal weight. Many underweight individuals aged 10-45 years, with the highest proportion at the age of 20-25 years. The classification results show that men have a higher likelihood of suffering from obesity than women. Therefore, obesity prevention needs to be done, one of which is by applying a healthy lifestyle.

Keywords: BMI, Prediction, Obesity, K-Means

© 2024 Journal of DINDA

1. Introduction

Obesity is caused by excessive accumulation of fat tissue in the body. This happens because of the imbalance between incoming energy and outgoing energy [1]. Obesity itself is an increasingly serious health problem around the world. Even the World Health Organization (WHO) has declared that obesity is a global epidemic. From the prevalence and consequences of the obesity Therefore, it is a health problem that must be addressed epidemic, immediate treatment is needed. One of them immediately [2]. The Ministry of Health of the Republic is to take a computational approach to make predictions of Indonesia (Kemkes RI) announced that the number of between someone who is obese and who is not [8]. obese people worldwide has more than doubled since Where someone can check the level of obesity 1980. More than 1.9 billion adults over the age of 18 are independently. If the results of independent examination obese [3].

A commonly used method to measure obesity rates is body mass index (BMI), which is calculated by dividing body weight (kg) by height (meters) [4]. A person with One of them uses grouping techniques with the a BMI of 30 or higher is generally considered obese. clustering method. Clustering is a method of finding and People with a BMI of 25 or higher are considered grouping data with similar characteristics among each overweight [5]. Obesity is one of the causative factors of data set [10]. The group or cluster obtained becomes various degenerative diseases such as heart disease and useful information for the user's decision-making stroke. This disease is the leading cause of death of the process [11]. world's population, especially in the elderly group. In

addition, obesity increases the risk of bone and joint damage [6]. In addition, the increasing prevalence of global obesity will also increase mortality and morbidity at a relatively young age. The consequences of this obesity epidemic will have an impact on the degree of Public Health [7].

are found symptoms of diseases such as obesity, then the community can continue the examination to the doctor [9].

Received: 08-01-2024 | Revised: 15-02-2024 | Published: 15-02-2024

cluster analysis is a non-hierarchical cluster analysis and Yudia (2021) highlight the risk of complications in method that seeks to divide existing objects into one or obese pregnant women, emphasizing the need for more clusters or groups of objects based on their obesity monitoring and management during pregnancy characteristics, so that objects that have the same [23]. characteristics are grouped in the same cluster and similar objects have different characteristics will be grouped into other clusters [12]. A few previous studies have consistently demonstrated the use of K-Means clustering methods in various contexts. Research by [13], using K-Means clustering to group the spread of diarrhea. Meanwhile research by [14], illustrates the success of this method in the classification of nutritional value of toddlers. Such positive findings demonstrate the adaptive ability of K-Means clustering in handling different types of data.

Among them are Li Li, Qifa Song, and Xi Yang (2020) conducted two studies related to obesity. The first study used K-means clustering and quantile transformations in In this study we used datasets from kaggle. It is used to metabolic data to classify overweight and obese classify the difference between underweight and individuals. The results show hope for accurate overweight people. In this study, data was processed handling. The second study, also by Li Li, Qifa Song, using Data Mining techniques with the K-Means and Xi Yang, focused on classifying obese patients method. based on insulin resistance and insulin release by Kmeans clustering method using HOMA-IR and IGI 30 minutes [15]-[16].

Furthermore, Vervoort, T. Naets, L. Goossens, S. Verbeken, L. Claes, A. Tanghe, and C. Braet (2022) examined the relationship of emotional eating and obesity in children. The results showed that emotional eating was associated with higher body weight and poor weight loss outcomes [17]. I Made Satria Bimantara and I Wayan Supriana (2022) in their research used Euclidean distance and K-means indexing methods in machine learning and data mining to estimate obesity rates with a Case Based Reasoning (CBR) approach [3]. Other research conducted by M. G. Ahamad, M. F. Ahmed, and M. Y. Uddin (2016) utilizing Weka in exploration for automatic classification, regression, and feature selection in bioinformatics. Their research deals with the analysis of risk factors for diabetes, hypertension, and obesity [18].

Research by Pebriani, Frethernety, and Trinovita (2022) found a positive relationship between junk food consumption and obesity through a systematic review of 15 journals. Mahdiah [19], Hadi, and Susetyowati (2004) highlight the change in diet to junk food because of technological developments, supporting the need for prevention of adolescent obesity in cities and villages [20]. Ni Putu Lia Juliantini and I Gusti Lanang Sidiartha (2014) confirmed the relationship between parental obesity and child obesity [21]. Sesilia Effendy, Gunawan, Argoputra, Anggraeni, Abraham, and Fenty (2018) found the complexity of factors affecting obesity, without a significant relationship between physical

K-Means is one of the clustering algorithms. K-Means activity and obesity at the study site [22]. Mulyani, Ngo,

This paper aims to determine the difference between someone who is obese and who is not and classify the level of obesity by utilizing the K-Means clustering algorithm to group them. The move was taken as part of obesity prevention efforts, with the hope that a deeper understanding of the distribution of obesity within specific categories could help design more specific and effective interventions. Using this approach, it is hoped that this study can contribute to our understanding of the complexities of obesity and encourage more precise and targeted preventive measures.

2. **Research Methods**

2.1. Dataset

The dataset used in this study was sourced from kaggle. This dataset consists of 110 data containing information ranging from id, age, gender, height, weight, BMI (Body Mass Index), and obesity classification labels which can be normal weight, underweight, or overweight.

Table 1. Dataset Obesity

ID	Age	Gender	Height	Weight	BMI	Label
						Normal
1	25	Male	175	80	25.3	Weight
						Normal
2	30	Female	160	60	22.5	Weight
						Overweigh
3	35	Male	180	90	27.3	t
						Underweig
4	40	Female	150	50	20	ht
5	45	Male	190	100	31.2	Obese
						Underweig
6	50	Female	140	40	16.7	ht
7	55	Male	200	110	34.2	Obese
						Underweig
8	60	Female	130	30	13.3	ht

Journal of Dinda : Data Science, Information Technology, and Data Analytics

Vol. 4 No. 1 (2024) 14 – 22

Aditya Wildan^{1*}, Helmy Akmal Burhansyah², Choki Ferdiansyah³ Journal of Dinda: **Data Science, Information Technology, and Data Analytics** Vol. 4 No. 1 (2024) 14 – 22

9	65	Male	210	120	37.2	Obese	30	108	Male	210	120	37.2	Obese
						Underweig							Normal
10	70	Female	120	20	10	ht	31	19	Male	175	75	24.2	Weight
						Normal							Normal
11	18	Male	175	70	23.4	Weight	32	24	Female	160	55	21.2	Weight
						Underweig							Overweigh
12	23	Female	160	50	20	ht	33	29	Male	180	85	26.1	t
						Normal							Overweigh
13	28	Male	180	80	25.3	Weight	35	39	Male	190	95	27	t
						Normal							Overweigh
14	33	Female	150	60	22.5	Weight	36	44	Female	140	75	25	t
						Overweigh	37	49	Male	200	105	28.9	Obese
15	38	Male	190	90	27.3	t							Overweigh
						Underweig	38	54	Female	130	85	27.5	t
16	43	Female	140	50	20	ht	39	59	Male	210	115	30.8	Obese
17	48	Male	200	100	31.2	Obese							Overweigh
						Underweig	40	64	Female	120	95	29.1	t
19	53	Female	130	40	16.7	ht							Normal
20	58	Male	210	110	34.2	Obese	41	17	Male	175	65	22.7	Weight
						Underweig							Underweig
21	63	Female	120	30	13.3	ht	42	22	Female	160	45	18.7	ht
						Normal							Normal
22	68	Male	175	80	25.3	Weight	43	27	Male	180	75	24.2	Weight
						Normal							Normal
23	73	Female	160	60	22.5	Weight	44	32	Female	150	55	21.2	Weight
						Overweigh							Overweigh
24	78	Male	180	90	27.3	t	45	37	Male	190	85	26.1	t
						Underweig							Normal
25	83	Female	150	50	20	ht	46	42	Female	140	65	22.7	Weight
26	88	Male	190	100	31.2	Obese							Overweigh
						Underweig	47	47	Male	200	95	27	t
27	93	Female	140	40	16.7	ht							Overweigh
28	98	Male	200	110	34.2	Obese	48	52	Female	130	75	25	t
						Underweig	49	57	Male	210	105	28.9	Obese
29	103	Female	130	30	13.3	ht							Overweigh
							50	62	Female	120	85	27.5	t

 $\label{eq:constraint} Journal of Dinda: {\bf Data Science, Information Technology, and Data Analytics} \\ Vol.4 No. 1 (2024) 14-22$

Aditya Wildan^{1*}, Helmy Akmal Burhansyah², Choki Ferdiansyah³ Journal of Dinda: **Data Science, Information Technology, and Data Analytics** Vol. 4 No. 1 (2024) 14 – 22

51 67 Male 175 65 22.7 Weight 69 56 Male 210 95 27 t 52 72 Female 160 45 18.7 ht 70 61 Female 120 75 25 t 53 77 Male 180 75 24.2 Weight 71 155 Male 175 455 18.7 ht 54 82 Female 150 55 21.2 Weight 72 20 Female 160 30 13.3 ht 55 87 Male 190 85 26.1 t 73 25 $Male$ 180 55 21.2 $Normal$ 55 87 Male 190 85 26.1 t 73 25 $Male$ 180 55 21.2 $Normal$ 56 92 Female 140 65 22.7 $Normal$ 74 <							Normal							Overweigh
5272Female1604518.7Underweig ht7061Female1207525Overweigh t5377Male1807524.2Normal Weight7115Male1754518.7Underweig ht5377Male1807524.2Weight7115Male1754518.7Underweig ht5482Female1505521.2Weight7220Female1603013.3Inderweig ht5587Male1908526.1Verweigh t7325Male1805521.2Normal Weight5692Female1406522.7Normal Weight7430Female1504016.7ht	51	67	Male	175	65	22.7	Weight	69	56	Male	210	95	27	t
52 72 Female 160 45 18.7 ht 70 61 Female 120 75 25 t 53 77 Male 180 75 24.2 Normal $Veight$ 71 15 Male 175 45 18.7 Underweig 54 82 Female 150 55 21.2 Weight 71 15 Male 160 30 13.3 116 54 82 Female 150 55 21.2 Weight 72 20 Female 160 30 13.3 116 55 87 Male 190 85 26.1 t 73 25 Male 180 55 21.2 $Veight$ 56 92 Female 140 65 22.7 $Veight$ 74 30 Female 150 40 16.7 Ht 10							Underweig							Overweigh
5377Male1807524.2Normal Weight7115Male1754518.7Underweight ht5482Female1505521.2Normal Weight7220Female1603013.3Underweight ht5482Female1505521.2Weight7220Female1603013.3Underweight ht5587Male1908526.1t7325Male1805521.2Normal Weight5692Female1406522.7Normal Weight7430Female1504016.7Underweight ht692Female1406522.7Weight7430Female1504016.7Underweight ht	52	72	Female	160	45	18.7	ht	70	61	Female	120	75	25	t
5377Male1807524.2Weight7115Male1754518.7ht5482Female1505521.2Weight7220Female1603013.3Underweig5482Female1505521.2Weight7220Female1603013.3Interweig5587Male1908526.1t7325Male1805521.2Weight5692Female1406522.7Weight7430Female1504016.7Underweig692Female1406522.7Weight7430Female1504016.7Interweig692Female1406522.7Weight7430Female1504016.7Interweig747							Normal							Underweig
5482Female1505521.2Normal Weight7220Female1603013.3Underweight ht5587Male1908526.1Overweigh t7325Male1805521.2Normal Weight5692Female1406522.7Normal Weight7430Female1504016.7Underweight Meight100 <td< td=""><td>53</td><td>77</td><td>Male</td><td>180</td><td>75</td><td>24.2</td><td>Weight</td><td>71</td><td>15</td><td>Male</td><td>175</td><td>45</td><td>18.7</td><td>ht</td></td<>	53	77	Male	180	75	24.2	Weight	71	15	Male	175	45	18.7	ht
5482Female1505521.2Weight7220Female1603013.3ht5587Male1908526.1Verweigh t7325Male1805521.2Normal Weight5692Female1406522.7Normal Weight7430Female1504016.7Underweigh ht							Normal							Underweig
5587Male1908526.1Overweigh t7325Male1805521.2Normal Weight5692Female1406522.7Normal Weight7430Female1504016.7Underweigh ht5692Female1406522.7Weight7430Female1504016.7Underweigh ht	54	82	Female	150	55	21.2	Weight	72	20	Female	160	30	13.3	ht
5587Male1908526.1t7325Male1805521.2Weight5692Female1406522.7Normal Weight7430Female1504016.7Underweight ht692Female1406522.7Weight7430Female1504016.7Normal ht							Overweigh							Normal
56 92 Female 140 65 22.7 Normal Weight 74 30 Female 150 40 16.7 Underweight 100	55	87	Male	190	85	26.1	t	73	25	Male	180	55	21.2	Weight
56 92 Female 140 65 22.7 Weight 74 30 Female 150 40 16.7 ht							Normal							Underweig
Overweigh Normal	56	92	Female	140	65	22.7	Weight	74	30	Female	150	40	16.7	ht
							Overweigh							Normal
57 97 Male 200 95 27 t 75 35 Male 190 65 22.7 Weight	57	97	Male	200	95	27	t	75	35	Male	190	65	22.7	Weight
Overweigh Underweig							Overweigh							Underweig
58 102 Female 130 75 25 t 76 40 Female 140 50 20 ht	58	102	Female	130	75	25	t	76	40	Female	140	50	20	ht
59 107 Male 210 105 28.9 Obese Image: Constraint of the second	59	107	Male	210	105	28.9	Obese							Normal
Overweigh 77 45 Male 200 75 24.2 Weight							Overweigh	77	45	Male	200	75	24.2	Weight
60 112 Female 120 85 27.5 t Image: Comparison of the temperature of temper	60	112	Female	120	85	27.5	t							Normal
Normal 78 50 Female 130 60 22.5 Weight							Normal	78	50	Female	130	60	22.5	Weight
61 16 Male 175 55 21.2 Weight Overweight Overweight	61	16	Male	175	55	21.2	Weight							Overweigh
Underweig 79 55 Male 210 85 26.1 t							Underweig	79	55	Male	210	85	26.1	t
62 21 Female 160 35 16.7 ht Normal	62	21	Female	160	35	16.7	ht							Normal
Normal 80 60 Female 120 70 23.4 Weight							Normal	80	60	Female	120	70	23.4	Weight
63 26 Male 180 65 22.7 Weight Underweig	63	26	Male	180	65	22.7	Weight							Underweig
Underweig 81 14 Male 175 35 16.7 ht							Underweig	81	14	Male	175	35	16.7	ht
64 31 Female 150 45 18.7 ht Underweig	64	31	Female	150	45	18.7	ht							Underweig
Normal 82 19 Female 160 25 10 ht							Normal	82	19	Female	160	25	10	ht
65 36 Male 190 75 24.2 Weight Underweig	65	36	Male	190	75	24.2	Weight							Underweig
Normal 83 24 Male 180 45 18.7 ht							Normal	83	24	Male	180	45	18.7	ht
66 41 Female 140 55 21.2 Weight Underweig	66	41	Female	140	55	21.2	Weight							Underweig
Overweigh 84 29 Female 150 30 13.3 ht	<u> </u>						Overweigh	84	29	Female	150	30	13.3	ht
67 46 Male 200 85 26.1 t Normal	67	46	Male	200	85	26.1	t							Normal
Normal 85 34 Male 190 55 21.2 Weight							Normal	85	34	Male	190	55	21.2	Weight
68 51 Female 130 65 22.7 Weight Underweig	68	51	Female	130	65	22.7	Weight							Underweig
86 13 Male 175 25 10 ht							5	86	13	Male	175	25	10	ht

 $\label{eq:constraint} Journal of Dinda: {\bf Data Science, Information Technology, and Data Analytics} \\ Vol.4 No. 1 (2024) 14-22$

Aditya Wildan^{1*}, Helmy Akmal Burhansyah², Choki Ferdiansyah³ Journal of Dinda: **Data Science, Information Technology, and Data Analytics** Vol. 4 No. 1 (2024) 14 – 22

						Underweig	10						Underweig
87	18	Female	160	20	8.3	ht	5	57	Female	120	25	10	ht
						Underweig	10						Underweig
88	23	Male	180	30	13.3	ht	6	11	Male	175	10	3.9	ht
						Underweig	10						Underweig
89	28	Female	150	25	10	ht	7	16	Female	160	10	3.9	ht
						Underweig	10						Underweig
90	33	Male	190	40	16.7	ht	8	21	Male	180	15	5.6	ht
						Underweig	10						Underweig
91	38	Female	140	35	16.7	ht	9	26	Female	150	15	5.6	ht
						Underweig	11						Underweig
92	43	Male	200	50	20	ht	0	31	Male	190	20	8.3	ht
						Underweig							
93	48	Female	130	40	16.7	ht	2.2.	Cluster	ring				
						Normal	Cluster is a collection of data objects that						that have
94	53	Male	210	55	21.2	Weight	different objects with other group data [14].					group and [4]. While	
						Underweig	g clustering is basically a method to find and grou that has similar characteristics (similarity) betwee data with another data. Clustering is one of th				group data		
95	58	Female	120	35	16.7	ht					of the data		
						Underweig	mini	ing met	thods that	is unsup thout trai	ervised, r	neanii	ng that this
96	12	Male	175	15	5.6	ht	a tea	icher (t	eacher) a	nd does n	ot require	an ou	utput targe
						Underweig	[10]	•					
97	17	Female	160	15	5.6	ht	2.3.	K-Mea	ns Cluste	ring			
						Underweig	K-M whe	leans 18 re the 1	s a metho modeling	d of analy	yzing data s without	a in D	ata Mining vision and
98	22	Male	180	20	8.3	ht	is or	ne meth	od that gr	oups data	in partiti	ons. T	his method
						Underweig	mini max	imizes	difference	es betwee es with of	en data in ther cluste	one ors.	cluster and
99	27	Female	150	20	8.3	ht	The	re are so	everal cha	racteristi	cs in the K	C-Mea	ns method
10						Underweig	inclu	uding:					-
0	32	Male	190	25	10	ht	1)) K-N	feans is a	simple gr	ouping m	ethod	that can be
10						Underweig	2) In c	ertain ty	pes of da	ata sets, I	K-Me	ans cannot
1	37	Female	140	25	10	ht		segr	nent data	properly	where t	he se	gmentation
10						Underweig	-	resu repr	esent the	characteri	istics of th	ip pa le natu	tterns that
2	42	Male	200	30	13.3	ht	2	the	data. Isang san	min into	mahlam		
10						Underweig	3	, K-N data	that cont	ains outli	problems ers.	s whe	n grouping
3	47	Female	130	30	13.3	ht							
10						Underweig	In g	general,	the K-N	Aeans m	ethod use	es the	following
4	52	Male	210	35	16.7	ht	aigo	num:					

$\label{eq:constraint} Journal of Dinda: {\bf Data Science, Information Technology, and Data Analytics} \\ Vol.4 No. 1 (2024) 14-22$

- 1) determination of the number of k clusters is carried those who were overweight to those who were not. out by several factors such as theoretical and conceptual considerations proposed to determine how many clusters.
- 2) Randomly generate the initial Centroid k (cluster center point). To determine the initial centroid is done randomly from several objects available as many as k clusters, to calculate the next i-th cluster centroid, using the following formula:

$$v = \frac{\sum_{i=1}^{n} X_i}{n}$$
; i = 1, 2, 3, ... n (1)

Where:

v = centroid on cluster

Xi = i-th object

N = The number of objects or the number of objects that are members of the cluster

Calculate the distance of each object to each centroid of each cluster. Then calculate the distance between objects with centroids, in this study using Euclidean Distance.

$$d(x,y) = ||x - y|| = \sqrt{\sum_{i=1}^{n} (Xi - Yi)^2}$$
(2)

Where:

Xi = i-th x object Yi = Data i-thN = The number of objects

- 3) Allocate each object into the closest centroid. Iterate, then determine the position of the new centroid using the equation.
- 4) Repeat step 3 if the new centroid positions are not the same.

The point merging process is done by comparing the task set matrix in the previous iteration with the task set matrix in the current iteration. If the results are the same then the k-means cluster analysis algorithm is already convergent, but if it is different than it has not converged so it needs to be done the next iteration.

3. Results and Discussion

We used 110 obesity data from kaggle. This data contains information ranging from id, age, sex, height, weight, BMI (Body Mass Index), and obesity classification labels which can be normal weight, underweight, or overweight. The purpose of this study

Specify k as the number of clusters in the form. The was to find differences and classify into clusters from

From the data in table 1, several analyses of the data will be carried out.





Figure 2. Distribution of Sex

The age distribution of the study in figure 1 shows that the age range ranges from 10 - 60 years. Where the ratio between men and women is almost equal or almost half. Figure 2 also showed that more than half of the women were underweight and none were obese.

The application of the K-Means algorithm successfully divided the study participants into four clusters based on certain characteristics, such as age, gender, and BMI values. This division provides deeper insight into patterns that might influence prediction of obesity classifications, helping to be more specific in clustering approaches.

Journal of Dinda : Data Science, Information Technology, and Data Analytics Vol. 4 No. 1 (2024) 14 - 22

Table 1. Clustering								
n_cluster	Correctly labeled	accuracy						
3	31	0,29						
4	56	0,52						
5	16	0,15						

Based on table 2, the number of cluster 3 is 31 correctly labeled data where the accuracy is 0.29. While in the number of clusters equal to 5, there are only 16 data with an accuracy level of 0.15. Then the number of cluster 4 is the highest level of accuracy with labeled data is 56 data.

Therefore, in this method 4 clusters are used, as shown in figure 3.



Furthermore, classification was carried out based on the 4 clusters with data in the form of gender, age, and obesity level labels. Based on figures 4, 5, and 6, it is found that the four clusters are categorized, as follows:

1) Cluster 0

In this cluster, there are only women, with an age range ranging from 45 to 60 years. Relatively thin to normal weight.

2) Cluster 1

In this cluster, there are only men, with an age range of more than 40 years and 55 to 60 years. People in this cluster are overweight or obese.

- Cluster 2 Women aged 15-70 years make up the majority in this group, with women aged 55-60 years as the highest proportion. In general, they have a normal weight.
- 4) Cluster 3

Most underweight individuals in the study were aged 10-45 years, with the highest proportion at the age of 20-25 years.



Figure 4. Classification Based on Gender



Figure 5. Classification Based on Age



Figure 6. Classification Based on Label

4. Conclusion

The results of this study suggest that this approach may contribute to our understanding of the complexities of obesity and encourage more precise and targeted preventive measures. Using the K-Means clustering algorithm, the study was successful in grouping obesity data into several similar groups, which could aid in

Journal of Dinda : Data Science, Information Technology, and Data Analytics Vol. 4 No. 1 (2024) 14 – 22 medical decision-making and obesity prevention.

Where this study found that obesity levels can be classified into four clusters based on three parameters, namely gender, age, and obesity level labels. The classification results show that men have a higher likelihood of suffering from obesity than women. Therefore, obesity prevention needs to be done, one of which is by applying a healthy lifestyle.

References

- S. K. Saraswati *et al.*, "Literature Review: Faktor Risiko Penyebab Obesitas," *Media Kesehat. Masy. Indones.*, vol. 20, no. 1, pp. 70–74, 2021, doi: 10.14710/mkmi.20.1.70-74.
- [2] M. Mauliza, "Obesitas Dan Pengaruhnya Terhadap Kardiovaskular," AVERROUS J. Kedokt. dan Kesehat. Malikussaleh, vol. 4, no. 2, p. 89, 2018, doi: 10.29103/averrous.v4i2.1040.
- [3] I. M. S. Bimantara and I. W. Supriana, "Case Based Reasoning (Cbr) for Obesity Level Estimation Using K-Means Indexing Method," *J. Ilm. Kursor*, vol. 11, no. 4, pp. 145–156, 2023, [Online]. Available: http://www.kursorjournal.org/index.php/kursor/artic le/view/268%0Ahttps://www.kursorjournal.org/inde x.php/kursor/article/download/268/140
- [4] H. Harahap, Y. Widodo, and S. Mulyati, "Penggunaan Berbagai Cut-Off Indeks Massa Tubuh Sebagai Indikator Obesitas Terkait Penyakit Degeneratif Di Indonesia," *Gizi Indones.*, vol. 28, no. 2, 2014, doi: 10.36457/gizindo.v28i2.20.
- [5] H. Ariyanti and D. I. Angraini, "Penatalaksanaan Holistik Obesitas di Puskesmas Rawat Inap Kemiling," *Majority*, vol. 7, no. 3, pp. 191–196, 2018, [Online]. Available: http://juke.kedokteran.unila.ac.id/index.php/majorit y/article/view/2075/2043
- [6] E. Supartini, P. F. Rahmah, F. F. Rahmadanti, M. Antikasari, and R. S. Pontoh, "ANALYSIS OF OBESITY RATES ON CALORIE CONSUMPTION OF SOME FOODS IN 40 ASIAN COUNTRIES Obesity occurs when the body becomes obese caused by a buildup of adipose (adipocytes, i.e., particular fat tissue stored by the body), which is excessive and cause," pp. 1–21, 2022.
- [7] M. Masrul, "Epidemi obesitas dan dampaknya terhadap status kesehatan masyarakat serta sosial ekonomi bangsa," *Maj. Kedokt. Andalas*, vol. 41, no.

3, p. 152, 2018, doi: 10.25077/mka.v41.i3.p152-162.2018.

- [8] R. C. Cervantes and U. M. Palacio, "Estimation of obesity levels based on computational intelligence," *Informatics Med. Unlocked*, vol. 21, no. November, 2020, doi: 10.1016/j.imu.2020.100472.
- [9] S. Y. Sibi, A. R. Widiarti, and U. S. Dharma, "Klasifikasi Tingkat Obesitas mempergunakan Algoritma KNN," *Semin. Nas. Corisindo*, vol. 7, no. 2, pp. 370–375, 2022.
- [10] J. O. Ong, "Implementasi Algotritma K-means clustering untuk menentukan strategi marketing president university," *J. Ilm. Tek. Ind.*, vol. vol.12, no, no. juni, pp. 10–20, 2013.
- [11] A. Nur Khormarudin, "Teknik Data Mining: Algoritma K-Means Clustering," J. Ilmu Komput., pp. 1–12, 2016, [Online]. Available: https://ilmukomputer.org/category/datamining/
- [12] Ediyanto, M. N. Mara, and N. Satyahadewi, "Pengklasifikasian karakteristik dengan metode kmeans cluster analysis," *Bul. Ilm. Mat. Stat. dan Ter.*, vol. 02, no. 2, pp. 133–136, 2013.
- [13] F. Nasari and C. J. M. Sianturi, "Penerapan Algoritma K-Means Clustering Untuk Pengelompokkan Penyebaran Diare Di Kabupaten Langkat," *CogITo Smart J.*, vol. 2, no. 2, pp. 108– 119, 2016, doi: 10.31154/cogito.v2i2.19.108-119.
- [14] Ramadhan, Nur Ghaniaviyanto. "Indonesian online news topics classification using Word2Vec and Knearest neighbor." Jurnal RESTI (Rekayasa Sistem Dan Teknologi Informasi) 5.6 (2021): 1083-1089.
- [15] L. Li, Q. Song, and X. Yang, "K-means clustering of overweight and obese population using quantiletransformed metabolic data," *Diabetes, Metab. Syndr. Obes.*, vol. 12, pp. 1573–1582, 2019, doi: 10.2147/DMSO.S206640.
- [16] L. Li, Q. Song, and X. Yang, "Categorization of βcell capacity in patients with obesity via ogtt using kmeans clustering," *Endocrine Connections*, vol. 9, no. 2. pp. 135–143, 2020. doi: 10.1530/EC-19-0476.
- [17] L. Vervoort *et al.*, "Subtyping youngsters with obesity: A theory-based cluster analysis," *Appetite*, vol. 168, no. August 2020, p. 105723, 2022, doi: 10.1016/j.appet.2021.105723.
- [18] M. G. Ahamad, M. F. Ahmed, and M. Y. Uddin,

Journal of Dinda : Data Science, Information Technology, and Data Analytics Vol. 4 No. 1 (2024) 14 – 22

"Clustering as Data Mining Technique in Risk Factors Analysis of Diabetes, Hypertension and Obesity.," Eur. J. Eng. Technol. Res., vol. 1, no. 6, pp. 88–93, 2018, doi: 10.24018/ejeng.2016.1.6.202.

- [19] L. Pebriani, A. Frethernety, and E. Trinovita, "Studi Literatur: Pengaruh Konsumsi Junk Food terhadap Obesitas," J. Surya Med., vol. 8, no. 2, pp. 270-280, 2022, doi: 10.33084/jsm.v8i2.3103.
- [20] Mahdiah, H. Hadi, and Susetvowati, "Prevalensi kejadian obesitas pada remaja SLTP kota dan desa di Daerah Istimewa Yogyakarta," JURNAL GIZI KLINIK INDONESIA, vol. 1. pp. 69-77, 2004. [Online]. Available: https://jurnal.ugm.ac.id/jgki/article/view/17397/113 23
- [21] I. G. L. Sidiartha and N. P. L. Juliantini, "Hubungan Riwayat Obesitas Pada Orangtua Dengan Kejadian

Obesitas Pada Anak Sekolah Dasar," E-Jurnal Med. Udayana, vol. 3, no. 12, pp. 1–13, 2018.

- [22] S. Effendy, M. F. Gunawan, D. Lintang, A. Argoputra, P. D. Anggraeni, and Y. B. Abraham, "the Relationship Between Physical Activity and Obesity Based on Body Fat Percentage in Banjaroyo Village," Int. Phys. Act. J. Farm. Sains dan Komunitas, vol. 15, no. 1, pp. 29-36, 2018, [Online]. Available: http://dx.doi.org/10.24071/jpsc.151963.
- obesitas dan hubungan konsumsi fast food dengan [23] L. Mulyani, N. F. Ngo, and R. C. P. Yudia, "Hubungan Obesitas dengan Komplikasi Maternal dan Luaran Perinatal," J. Sains dan Kesehat., vol. 3, 2. 343-350, 2021, doi: no. pp. 10.25026/jsk.v3i2.483.
 - [24] W. Van Der Aalst, Process Mining Data Science In Action. Springer Heidelberg New York Dordrecht London, 2016.