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Combination of Decision Support Systems and Geographic Information Systems in Determining Undernutrition Status Using Deep Learning And *K-Means Clustering*

Mohammad Ilham Bahri[a], Muhammad Aswin[b], M. Fauzan Edy Purnomo[c]

[a] Departement of Electrical Engineering Brawijaya University, Malang, Indonesia
[b] Departement of Electrical Engineering Brawijaya University, Malang, Indonesia
[c] Departement of Electrical Engineering Brawijaya University, Malang, Indonesia

A B S T R A C T

The nutritional status of toddlers is a factor that needs to be considered in maintaining their health because toddlerhood is a developmental period that is vulnerable to nutrition. Death cases in toddlers are one factor in the lack of monitoring by local governments. It is necessary to carry out activities to observe and anticipate problems to take action as early as possible. This problem can be solved using the help of Decision Support Systems and Geographic Information Systems. Machine learning-based deep learning methods are employed as alternative algorithms for Decision Support Systems. Deep learning is considered a very promising approach due to its ability to analyze and extract patterns from data, afterwards applying these patterns to address following challenges. The selection of a Geographic Information Systems was conducted by employing the k-means clustering technique in order to create a visual representation of the zone groupings within each region. The accuracy of the deep learning method for determining nutritional status was found to be 95.24%. In the context of mapping regional zone groupings, it is noteworthy that the k-means clustering method exhibits a remarkable accuracy rate of 100% in relation to the true value. Based on the obtained findings, it can be inferred that the deep learning and k-means clustering techniques exhibit a high level of accuracy in discerning nutritional status and delineating regional zone groupings.

Keywords: *Deep Learning, K-Means Clustering*, Decision Support System, Determining of Nutrition Status, Mapping, Geographical Information Systems.

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1. Introduction

Malnutrition can be considered a significant problem in developing countries, including Indonesia, especially for toddlers. According to [1], nutritional status in toddlers is a factor that needs to be considered in maintaining their health. Death cases in toddlers are one factor in the lack of monitoring by local governments. In accordance with Presidential Decree Number 72 of 2021 pertaining to the expeditious mitigation of stunting, it is imperative to undertake proactive measures to monitor and preempt potential challenges, hence enabling prompt intervention.

Therefore, several main criteria are needed as supporting criteria that will be considered when deciding to determine the nutritional status of children under five, as explained by [2].

Apart from the main criteria that have been determined, in general, supporting criteria will also be determined, which will be taken into consideration when making decisions to determine nutritional status. From the results of determining nutritional status, regional zone groupings will be mapped based on the number of nutritional statuses in each region. The problem that arises from these criteria is that there are differences in the data form. Hence, a processing process is it is needed for the data. The condition of the data also exacerbates this often incomplete, complicating the ordinary decision-making process. Each toddler can only receive one nutritional status, and in regional zone grouping mapping, you can only get one recommended zone status for each region.

Quick decision-making can be done with a Decision Support Systems [3]. In his proposal, [4] this study demonstrates the use of decision-making principles through the utilization of a computerized system. The impact of machine learning advancements on the deployment of Decision Support Systems is evident, as exemplified by [5] the utilization of deep learning, a data processing approach that enables computers to emulate human brain functionality [6]. In his research, [7] only discussed determining nutritional status using a perceptron. The advancements in machine learning techniques have a significant impact on Decision Support Systems, as evidenced by various studies conducted in the field [8]. However, in previous research, no one has specifically discussed deep learning methods concerning Decision Support Systems, which will later be combined with Geographic Information Systems for mapping regional zone groupings.

* *Corresponding author.* Phone : +6282141441453
E-mail address: ilhambahri@student.ub.ac.id

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According to [9], a Geographic Information Systems is a computer system designed to manage geographic data and present it as geographic information in digital maps.

Then, the Geographic Information System for mapping regional zone groupings uses the k-means clustering method. According to [10], data with similarities with other data will be grouped into one group, while data with different characteristics will be combined into another group.

This research will apply deep learning techniques, namely using neurons arranged in several layers to form a Decision Support Systems for determining nutritional status in toddlers as well as a Geographic Information Systems for mapping regional zone groupings using the k-means clustering method.

2. Material and Methods

2.1. Deep Learning

Artificial Neural Network is a complex model analogous to the workings of the biological nervous system. An Artificial Neural Network is comprised of interconnected neuron units, with each link facilitating the transmission of impulses. Every individual neuron will undergo signal processing and generate an output based on the outcomes of this processing. The signals within the synaptic connections among these neurons constitute the fundamental values and the resultant outcome of their summation. The outcomes of neuronal processing are included into a non-linear function. In every synaptic connection, it is customary to assign a weight that serves to modulate the magnitude of input received by each individual neuron. One of the initial models offered for these neurons is the perceptron model, which was first developed by [11]. This model is shown in Figure 1.

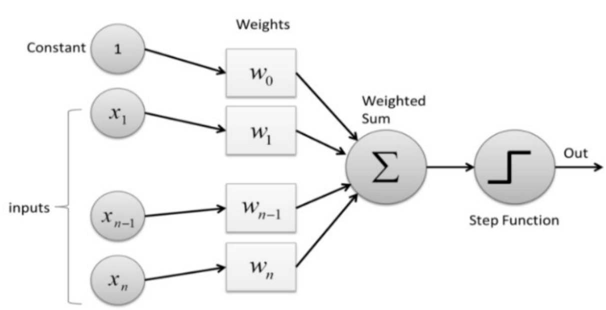

Figure 1. Perceptron model

The perceptron was first seen as a promising tool due to its ability to provide a computational framework that facilitated the acquisition of intrinsic patterns in a given physical occurrence. However, a limitation was identified when it was seen that the perceptron exhibited an inability to effectively tackle a very simple problem, specifically the XOR problem. This discovery subsequently guides the use of perceptron in the field of deep learning, wherein the perceptron is organized into many layers. Each layer is responsible for solving a specific problem or generating a distinct feature by amalgamating various features from the preceding layer. The utilization of deep learning techniques enhances the overall efficacy of this model.

Deep learning is a subset of machine learning techniques that relies on neural networks as its foundational framework. Deep learning has the capability to be employed in several modes, namely supervised, semi-supervised, or unsupervised. The utilization of deep learning can be characterized by the specific architectural frameworks employed, such as deep neural networks, deep belief networks, recurrent neural networks, and convolutional neural networks. These architectures have been successfully employed in various domains, including image recognition, voice recognition, natural language processing (NLP), translation, bioinformatics, drug design, and medical image analysis. In prior studies conducted by [12], It was additionally determined that the utilization of deep learning in image categorization and pattern recognition resulted in a performance surpassing that of human recognition.

The terminology deep in the context of deep learning pertains to the employment of multiple layers inside the neural network architecture that is employed. In the context of shallow networks, it is observed that there is a sole hidden layer that resides between the input and output layers, as visually depicted in Figure 2. Meanwhile, more than one hidden layer is used in deep learning architecture, as shown in Figure 3.

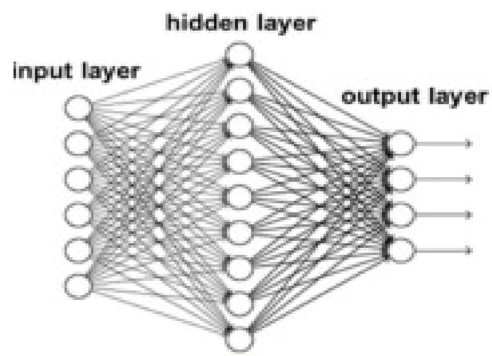

Figure 2. Shallow learning architecture

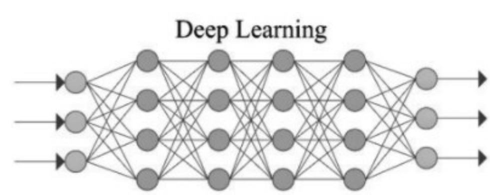

Figure 3. Deep learning architecture

There exist multiple computational techniques for conducting this training, among which is the Gradient Descent (GD) method, as originally suggested in [13], The objective is to enhance the performance of a function through an iterative process that involves adjusting the input in a manner that aligns the direction of the tangent to the curve of the function being optimized with the desired direction. During the training process of deep learning, this particular method aims to minimize the cost function. One illustrative instance involves the representation of the cost function for a deep learning model, which may be mathematically stated as Equation 1.

$$f(m,b) = \frac{1}{N}\sum_{i=1}^{n}\left(y_i - (mx_i + b)\right)^2 \quad (1)$$

Note:
m : weight parameters
b : bias parameters
n : number of data
i : data index

By utilizing the above equation as a cost function, it is possible to determine the gradient of the function at a specific position using Equation 2.

$$f'(m,b) = \begin{bmatrix} \frac{df}{dm} \\ \frac{df}{db} \end{bmatrix} = \begin{bmatrix} \frac{1}{N}\sum -2x_i(y_i - (mx_i + b)) \\ \frac{1}{N}\sum -2(y_i - (mx_i + b)) \end{bmatrix} \quad (2)$$

Note:
m : weight parameters
b : bias parameters
n : number of data
i : data index

In order to get the gradient value, it is necessary to iterate through all the points utilized for the m and b values, and subsequently compute the partial derivative of the equation.

2.2. K-means Clustering

The k-means clustering approach is utilized to establish regional zone groupings within the context of Geographic Information Systems. According to [14], grouping is a data mining technique used to analyze data to solve problems in data grouping. This model is shown in Figure 4.

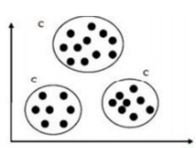

Figure 4. K-means clustering model

Data with similar data will be grouped into one group, while data with different characteristics will be combined into another group using Equation 3.

$$d_{in} = \sqrt{\sum_{j=1}^{m}\left(x_{ij} - k_{nj}\right)^2} \quad (3)$$

Note:
d_{in} : distance from the data to i to the center point of the group to n
m : many features
x_{ij} : data to i feature to j
k_{nj} : central data of group n

Update the group center value by calculating the average value of each group member using Equation 4.

$$k_{ij} = \frac{\sum_{h=1}^{n} y_{hj}}{n} \quad (4)$$

Note:
K_{ij} : Center of the i the group of feature j
n : Number of all group member
y_{hj} : data to h the feature j in group i

2.3 Confusion matrix

The confusion matrix is a tabular representation that presents the classification outcomes of test data, indicating the count of correctly classified instances as well as the count of incorrectly classified instances. According to [15], a matrix is a tabular representation that provides a comprehensive evaluation of the efficacy of a certain algorithm. In the matrix, each row corresponds to the true class of the data, while each column corresponds to the anticipated class of the data (or vice versa). The matrix is explained in Table 1.

Table 1. *Confusion matrix*

	Positive Prediction	Negative Prediction
Actual Positive	TP	FP
Actual Negative	FN	TN

The use of the confusion matrix in calculating precision, recall, and accuracy in this research can be measured by the value produced by the system against the actual value. According to [16], the analysis method for using the confusion matrix is to determine values such as precision, recall, and accuracy of the model created and trained by calculating Equation 5, Equation 6, and Equation 7.

$$Presisi = \frac{TP}{(TP+FP)}\, x\ 100\% \quad (5)$$

$$Recall = \frac{TP}{(TP+FN)}\, x\ 100\% \quad (6)$$

$$Akurasi = \frac{(TP+TN)}{(TP+TN+FP+FN)}\, x\ 100\% \quad (7)$$

Note:
TP = Means how much of the actual data class is positive, and the model also predicts positive.
TN = Means how much of the data class is negative, and the model predicts negative.
FP = Means how much of the actual data is of a hostile class, but the model predicts positive.

FN = Means how much of the actual data is positive, but the model predicts negative.

3. Research Methods

3.1 Data Validation

Two types of quantitative data will be used in this research: nutritional data obtained from the Health Service, which contains complete data for determining nutritional status. Then, the actual nutritional status data is determined and realized. This actual data on nutritional status will be used to measure the level of accuracy of the Decision Support Systems and Geographic Information Systems by comparing it with the actual decisions taken. Based on the source, these two primary data are obtained directly from the Health Service to determine nutritional status.

The data validation is carried out by passing all nutritional data through the data validation process. This process aims to ensure that all data used in the training process is valid. The data validation process is explained in Figure 5.

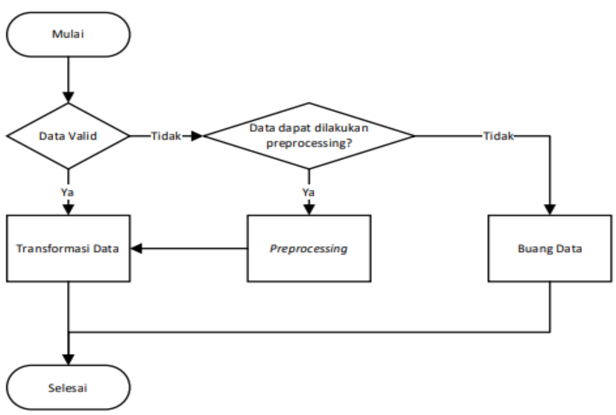

Figure 5. Data validation

Each data element is passed into the data validation process. The first element is to check whether it has a valid value. One data point is considered valid if all attributes are met. If this data is valid, the data will be immediately passed into a transformation process. Data that lacks attributes is considered invalid data. Then, undergo the following determination. In the subsequent determination, invalid data will be separated into categories that cannot be preprocessed. If preprocessing can be carried out, preprocessing will be carried out to fill in the empty data. If preprocessing cannot be carried out, the data will be discarded. Data that has gone through preprocessing will then be treated the same as valid data.

3.2 Deep Learning

Perceptron adds weights to each input and uses an activation function to calculate the output. This output is then compared with the desired result. To calculate the output, use Equation 8 and Equation 9.

$$y\_in = b + \sum_i x_i w_i \tag{8}$$

$$y = \begin{cases} 1 \; jika \; y\_in > \theta \\ 0 \; jika - \theta \leq y\_in \leq \theta \\ -1 \; jika \; y\_in < -\theta \end{cases} \tag{9}$$

Note:
y : external element of the perceptron
x : percepton input element
b : bias
θ : theta
w : weight
i : input index

Meanwhile, comparing with the desired results or targets in the perceptron model uses Equation 10.

$$\begin{aligned} &jika \; y \neq t \\ &\qquad w_i(baru) = w_i(lama) + \alpha t x_i \\ &\qquad b(baru) = b(lama) + \alpha t \\ &jika \; y = t \\ &\qquad w_i(baru) = w_i(lama) \\ &\qquad b(baru) = b(lama) \end{aligned} \tag{10}$$

Note:
y : external element of the perceptron
x : perceptron input element
b : bias
w : weight
t : target
i : input index
a : alpha

Determine the classification results or total probability, namely the value with the most considerable multiplication result. The level of The Artificial Neural Network probability is carried out using probability calculations using Equation 11.

$$P(E) = \frac{k}{N} \, x \, 100\% \tag{11}$$

Note:
P : Probability
E : Event
k : Number of success events
N : Total number of successes

The input data is received by the model from the input layer, and subsequently transmitted to the processing layers, also known as hidden layers. The outcomes of the processing will thereafter be presented as a numerical value in the output section, representing either a likelihood value or a recommendation regarding the suitability of a toddler for inclusion in a nutritional category.

3.3 K-means Clustering

The grouping method that is often used is the k-means clustering method. This method can divide data into several groups. Data that has a level of compatibility between data will be grouped into one group, while data with different characteristics will be grouped into another group. By using this grouping, we can classify nutritional data from each region. Grouping this data uses Equation 12.

$$d_{in} = \sqrt{\sum_{j=1}^{m}\left(x_{ij} - k_{nj}\right)^2} \quad (12)$$

Note:
d_{in} : distance from the data to i to the center point of the group to n
m : banyaknya fitur
x_{ij} : data ke i fitur ke j
k_{nj} : data pusat kelompok ke n

Update the group center value by calculating the average value of each group member using Equation 13.

$$k_{ij} = \frac{\sum_{h=1}^{n} y_{hj}}{n} \quad (13)$$

Note:
K_{ij} : center of the i the group of feature j
n : the number of all group members
y_{hj} : data to h the feature j in group i

Repeat so that no data moves to another group or reaches the specified maximum repetition limit.

4. Result

At this juncture, the implemented model is executed. The optimization technique employed for achieving precision in this study is Adam, whilst the binary crossentropy approach is utilized for calculating the loss. The training of the complete model is conducted by utilizing the training parameters specified in Table 2.

Table 2. Model training parameters

Parameters	Value
Optimizer	*Adam*
Loss	*Binary_crossentropy*
Metrics	*Binary_accuracy*

Subsequently, the model underwent training to ascertain nutritional status. Training the model used several epochs of 500 and some batches of 100. The training results are shown in Figure 6 and Figure 7. The loss value was found to be 0.1601, with an accuracy value of 95.24%.

```
Epoch 493/500
10/10 [==============================] - 0s 4ms/step - loss: 0.1749 - accuracy: 0.9438
Epoch 494/500
10/10 [==============================] - 0s 4ms/step - loss: 0.1721 - accuracy: 0.9416
Epoch 495/500
10/10 [==============================] - 0s 4ms/step - loss: 0.1751 - accuracy: 0.9405
Epoch 496/500
10/10 [==============================] - 0s 4ms/step - loss: 0.1743 - accuracy: 0.9460
Epoch 497/500
10/10 [==============================] - 0s 4ms/step - loss: 0.1697 - accuracy: 0.9493
Epoch 498/500
10/10 [==============================] - 0s 4ms/step - loss: 0.1667 - accuracy: 0.9548
Epoch 499/500
10/10 [==============================] - 0s 4ms/step - loss: 0.1673 - accuracy: 0.9449
Epoch 500/500
10/10 [==============================] - 0s 5ms/step - loss: 0.1682 - accuracy: 0.9526
Masukkan Threshold: 0.5
8/8 [==============================] - 0s 1ms/step - loss: 0.1601 - accuracy: 0.9524
Loss: 0.1601, Accuracy: 0.9524
```

Figure 6. Training results using epoch 500 and batch 100

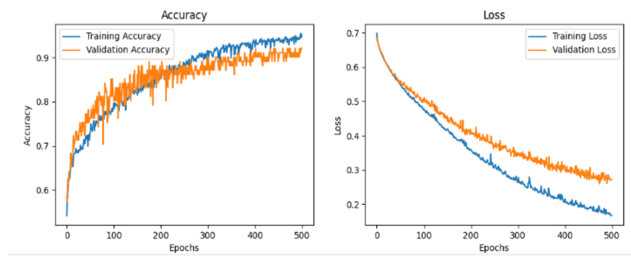

Figure 7. Graph of accuracy and loss values against epoch

Based on the findings shown in Table 5.3 and Table 5.4, it was seen that the system exhibited the capability to ascertain nutritional status. The total data used was 1260 data, of which 790 training data were determined precisely by the system created, and there were 458 test data determined precisely by the system created. This shows that the system has 2 errors in the test data for determining nutritional status, as shown in Table 3 and Table 4.

Table 3. Preliminary data

Status	Training Data	Test Data
Malnutrition	*416*	*178*
Good Nutrition	*384*	*282*

Table 4. Prediction results

Status	Training Data	Test Data
Malnutrition	*421*	*177*
Good Nutrition	*379*	*283*

Then, regional zone grouping using the k-means clustering method was carried out using data from the results of the nutritional status determination system using the deep learning method. The data that will be grouped is data on the number of malnutrition and good nutrition status from each sub-district in Sumenep Regency, shown in Table 5. Then, this data will be processed by the Geographic Information System using the k-means clustering method for grouping regional zones.

Table 5. Nutritional data for each sub-district

Sub-District	Malnutrition	Good Nutrition
Pragaan	14	6
Bluto	29	11
Saronggi	23	22
Kalianget	24	36
Sumenep	27	63
Batuan	22	33
Lenteng	34	36
Ganding	18	52
Guluk-Guluk	23	27
Pasongsongan	21	29
Ambunten	27	13
Rubaru	18	27
Manding	31	19
Batu Putih	28	22
Gapura	17	23
Batang-Batang	21	9
Gayam	8	7
Masalembu	18	22
Arjasa	10	5
Talango	18	52
Dungkek	28	42
Nonggunong	15	20
Raas	22	13
Sapeken	14	6
Dasuk	35	20
Kangean	20	30
Gili Genteng	33	17
Total	598	662

According to the data presented in Table 5, multiple input variables are considered, such as malnutrition and good nutrition data for each sub-district. These variables are utilized in the process of zone grouping, employing the k-means clustering approach.

Table 6 displays the results obtained from the application of the k-means clustering method, which involved many calculation procedures. The analysis revealed the presence of three distinct clusters, namely C1 (characterized by a high level of risk), C2 (exhibiting a medium level of vulnerability), and C3 (demonstrating a low level of vulnerability).

Table 6. Results of k-means clustering calculations

Sub-District	C1	C2	C3
Pragaan	0.10867060251801	0.50829352532382	0.57182931274339
Bluto	0.38787940821621	0.14568627181694	0.48999524372823
Saronggi	0.2648485091335	0.20250385312784	0.27324206208012
Kalianget	0.44819031179126	0.30641088284479	0.077596809227037
Sumenep	0.8693648201441	0.68790068833872	0.40638715100615
Batuan	0.37774813512859	0.30793650793651	0.096867542219784
Lenteng	0.64976130103855	0.27849793269157	0.34919855691162
Ganding	0.63384918412807	0.61282176568958	0.23311749006099
Guluk-Guluk	0.31748853490115	0.22879178091082	0.1946179336178
Pasonsongan	0.30851597327224	0.29416086117106	0.1623665993129
Ambunten	0.33032827013137	0.14033038797016	0.4391643270149
Rubaru	0.24398591869991	0.36041184694806	0.22204664265473
Manding	0.45686842634757	0.032684540130117	0.4115718445423
Batu Putih	0.39016778517798	0.065369080260235	0.32256624062638
Gapura	0.17504833423706	0.37446863335881	0.29139087490055
Batang-Batang	0.16731627831579	0.31081942918855	0.47846925651296
Gayam	0.22892633626065	0.66157541956853	0.64601622382975
Masalembu	0.16992613548361	0.34432372985286	0.29341062679863
Arjasa	0.19428582955813	0.61904761904762	0.63919718480941
Talango	0.63384918412807	0.61282176568958	0.23311749006099
Dungkek	0.59197435626551	0.35385078839601	0.18026211983335
Nonggunong	0.12235385385216	0.42857142857143	0.36163537732435
Raas	0.18760027599567	0.25414676266191	0.41429556638532
Sapeken	0.10867060251801	0.50829352532382	0.57182931274339
Dasuk	0.57182917566529	0.14285714285714	0.48166859553893
Kangean	0.30915774491332	0.32684540130117	0.15430857496061
Gili Genting	0.50702740514055	0.098053620390352	0.47290144562464

Based on the results, the system can determine zones based on clusters for each sub-district in Sumenep Regency. Three zones can be implemented by the system, where Table 7. red zone (C1) contains 9 sub-districts, Table 8. yellow zone (C2) contains 8 sub-districts, and Table 9. green zone (C3) contains 10 sub-districts as shown in Figure 8.

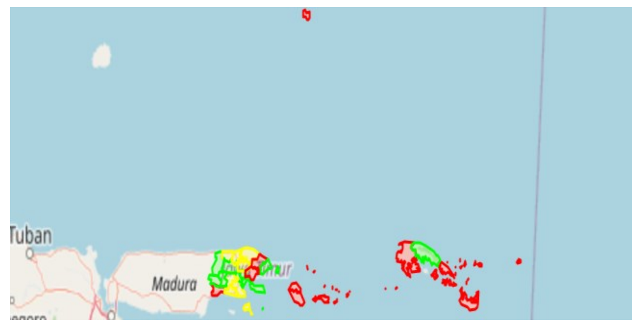

Figure 8. Zones of each sub-district

Table 7. *Cluster*-1 (C1)

Sub-District	C1	C2	C3
Pragaan	0.10867060251801	0.50829352532382	0.57182931274339
Gapura	0.17504833423706	0.37446863335881	0.29139087490055
Batang-Batang	0.16731627831579	0.31081942918855	0.47846925651296
Gayam	0.22892633626065	0.66157541956853	0.64601622382975
Masalembu	0.16992613548361	0.34432372985286	0.29341062679863
Arjasa	0.19428582955813	0.61904761904762	0.63919718480941
Nonggunong	0.12235385385216	0.42857142857143	0.36163537732435
Raas	0.18760027599567	0.25414676266191	0.41429556638532
Sapeken	0.10867060251801	0.50829352532382	0.57182931274339

Table 8. *Cluster*-2 (C2)

Sub-District	C1	C2	C3
Bluto	0.38787940821621	0.14568627181694	0.48999524372823
Saronggi	0.2648485091335	0.20250385312784	0.27324206208012
Lenteng	0.64976130103855	0.27849793269157	0.34919855691162
Ambunten	0.33032827013137	0.14033038797016	0.4391643270149
Manding	0.45686842634757	0.032684540130117	0.4115718445423
Batu Putih	0.39016778517798	0.065369080260235	0.32256624062638
Dasuk	0.57182917566529	0.14285714285714	0.48166859553893
Gili Genting	0.50702740514055	0.098053620390352	0.47290144562464

Table 9. *Cluster*-3 (C3)

Sub-District	C1	C2	C3
Kalianget	0.44819031179126	0.30641088284479	0.077596809227037
Sumenep	0.8693648201441	0.68790068833872	0.40638715100615
Batuan	0.37774813512859	0.30793650793651	0.096867542219784
Ganding	0.63384918412807	0.61282176568958	0.23311749006099
Guluk-Guluk	0.31748853490115	0.22879178091082	0.1946179336178
Pasonsongan	0.30851597327224	0.29416086117106	0.1623665993129
Rubaru	0.24398591869991	0.36041184694806	0.22204664265473
Talango	0.63384918412807	0.61282176568958	0.23311749006099
Dungkek	0.59197435626551	0.35385078839601	0.18026211983335
Kangean	0.30915774491332	0.32684540130117	0.15430857496061

Geographic Information Systems testing using the k-means clustering method uses a confusion matrix by calculating precision, recall, and accuracy values from the results obtained by the system against predetermined manual calculations, as explained in Table 10.

Table 10. *Confusion matrix*

	Positive Prediction	Negative Prediction
Actual Positive	17	0
Actual Negative	0	10

Calculating precision, recall, and accuracy values are explained in Equation 14, Equation 15, and Equation 16.

$$Presisi = \frac{17}{(17+0)}\, x\, 100\% = 100\% \tag{14}$$

$$Recall = \frac{17}{(17+0)}\, x\, 100\% = 100\% \tag{15}$$

$$Akurasi = \frac{(17+10)}{(17+10+0+0)}\, x\, 100\% = 100\% \tag{16}$$

Based on the test findings of the Geographic Information System utilizing the k-means clustering method, as presented in Table 10, it is evident that the system exhibits a high level of accuracy in determining the zone status of each sub-district 100%.

5. Conclusion

The Decision Support System model has been effectively developed utilizing the deep learning approach, resulting in a high level of accuracy 95.24%. Then, a Geographic Information System model using the k-means clustering method has been successfully created for grouping vulnerable areas with 100% accuracy performance.

Based on the findings, it can be inferred that the utilization of deep learning and k-means clustering techniques yields highly effective and precise outcomes in the assessment of nutritional status and the establishment of regional zone classifications.

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