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METHOD COMPARISON IN THE DECISION SUPPORT SYSTEM OF A SCHOLARSHIP SELECTION

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Abstract

Decision support system (DSS) as a computer-based system that assists in the decision-making process in which the current scholarship selection process has different targets and criteria for prospective scholarship recipients. This causes the decision-making process for scholarship selection to be complex, whereas in general scholarship selection is limited in time for decision-making. A possible solution is to use a DSS to improve consistency and speed up decision making. The available methods for making a DSS used in this study are the Analytical Hierarchy Process, TOPSIS, and the second model using a deep learning approach. The performance of the DSS will then be evaluated using a Confusion Matrix to determine the cost level of each DSS, and analyze the strengths and weaknesses of each DSS. The DSS model with the AHP-TOPSIS approach has been successfully created, with accuracy performance for the introduction of merit scholarship scheme data of 56.72%, bidikmisi scholarship data of 65.21%, and independent scholarship data of 95.87%. While the DSS model with a deep learning approach has been successfully created with accuracy performance which produces 71.93% achievement scholarship scheme data, 100% bidikmisi scholarship data, and 100% independent scholarship data.

Key words: Analytical Hierarchy Process, TOPSIS, Deep Learning, Confusion Matrix, Decision Support System.

INTRODUCTION

Scholarships are a form of financial support for students to support students to facilitate the completion of their learning activities[1]. Funding support for an educational scholarship program organized by a university can come from various sources, including from the government, from donors outside the university, as well as from independent college funds[2]. This scholarship program is generally provided, with the determination of the type of scholarship, based on the main criteria that are generally determined by the institution that funded the scholarship[3].

These criteria can be in the form of academic criteria, or non-academic criteria[4]. The problem that arises from these criteria is that there are differences in the form of these data, so a method is needed to evaluate these criteria. In addition to the problem of selection based on criteria, another problem in the selection process is that there is a lot of data, which needs to be analyzed in a short time, because generally there are deadlines that must be met in the scholarship application and administrative process[5]. A prospective scholarship recipient is only allowed to receive one scholarship (no multiple scholarships may occur) even if the recipient meets the criteria for more than one scholarship program[6]. This is also exacerbated by the condition of data that is often incomplete, which makes the ordinary decision-making process very complex.

Quick decision support, can be done with the support of a Decision Support System (DSS)[7][8][9][10]. In his proposal, [11] demonstrate the concept of decision support with the help of a computerized system. This use enables faster and more accurate decision making. There are several alternative methods available for DSS. The first is the AHP (Analytical Hierarchy Process) method[12]. Then, the relatively simpler SAW (Simple Additive Weighting) method is shown[13]. Then, another alternative is the TOPSIS approach[14]. On his research, [15] shows the incorporation of some of these methods in their decision making. The development of techniques in the field of machine learning, also affects the implementation in DSS, as shown [16]. The development of data mining techniques and their implementation in DSS is also shown in the research [17]. However, there are no previous studies that specifically discuss the deep learning approach that has the potential for better performance.

This research will apply a deep learning technique, which uses neurons arranged in several layers, to form a scholarship selection Decision Support System. As a performance reference, an AHP method-based DSS will also be made to compare performance, and see the strengths and weaknesses of these two methods in the scholarship selection DSS.

MATERIAL AND METHODS

Analytical Hierarchy Process (AHP)

Here we will discuss examples of using AHP in an example of decision support. This usage example is intended to provide a clearer picture of the use of AHP in the decision support process. This example is taken from an article about AHP [18]. In this example, a simple decision support will be given, regarding a person who is considering what the best job is after he gets a doctorate, regarding the selection of the best job.

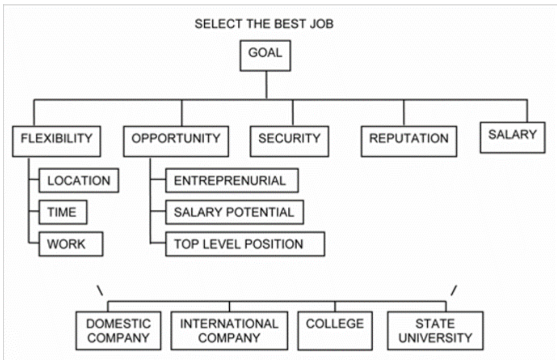

Fig 1. The best job decision support hierarchy
Source: Saaty (2008)

Deep Learning

Artificial Neural Network (ANN) consists of a collection of several units of connected neurons, where each connection can transmit a signal. Each neuron will perform processing of the received signal, and produce an output from the results of the processing. The signals in the connections between these neurons are real values, and the output of the sum of all neuronal processing results is entered into a non-linear function. In each relationship, there is usually a weight to match the input scale level for each neuron. One of the earliest proposed models of these neurons was the perceptron model which was first developed [19]. This model is show in Fig 2.

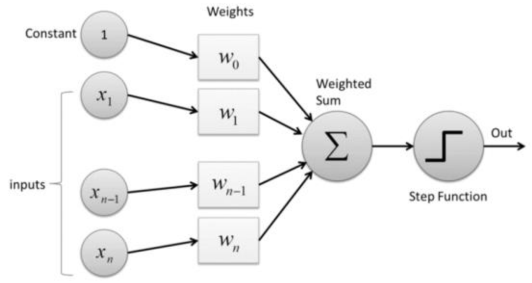

Fig 2. Perceptron model
Source: Sagar Sharma (2017)

The use of the perceptron was initially considered promising, because it offered a computational model that allows the learning process to derive the inherent pattern of a physical phenomenon. However, a problem was found, when it was found that the perceptron was not able to solve a very simple problem, namely the XOR problem. This finding then directs the use of perceptrons towards deep learning, where perceptrons are arranged into several layers, where each layer solves a problem or creates a feature which is a synthesis of several features in the previous layer. Deployment of deep learning improves the overall performance of this model.

Deep learning itself is part of the scope of machine learning methods based on neural networks. The use of deep learning can be supervised, semi-supervised, or unsupervised. The use of deep learning itself can be stated based on the architecture used, including deep neural networks, deep belief networks, recurrent neural networks, and convolutional neural networks, where these architectures have been applied to the realms of image recognition, speech recognition, natural language processing. NLP), translation, bioinformatics, drug design, to medical image analysis. In previous research [20], it is also concluded that in applications such as image classification and pattern recognition, deep learning performance is able to exceed human recognition performance.

The use of the term deep in deep learning refers to the use of multiple layers within the neural network architecture used. Meanwhile, in deep learning architecture, more than a hidden layer is used, as show in Fig 3.

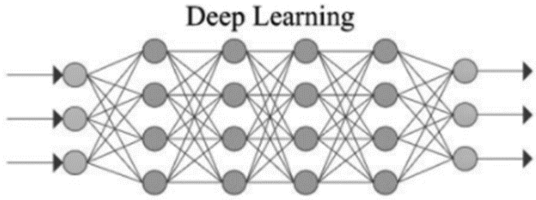

Fig 3. Deep learning architecture
Source: medium.com

There are several calculation methods to perform this training, one of which is the Gradient Descent method. Gradient Descent (GD) method as proposed [21], tries to optimize a function, by iteratively moving the input in the direction where the tangent to the curve of the function to be optimized leads to the most negative direction. In the deep learning training process, this approach is used to minimize the cost function. For example, if the cost function of a deep learning model, it can be expressed using Equation (1).

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

m : weight parameters
b : bias parameters
n : amount of data
i : data index

By using this equation as a cost function, we can find the gradient of the function at a point, using Equation (2).

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

m : weight parameters
b : bias parameters
n : amount of data
i : data index

So, to find the gradient, iterate over all the data points used, for the values of m and b, respectively, and calculate the partial derivative of the equation.

Technique For Others Reference by Similarity to Ideal Solution (TOPSIS)

Technique For Others Reference by Similarity to Ideal Solution (TOPSIS) is the proposed method[22]. The main idea of this concept is a solution that compromises the best alternative which is closest to the positive ideal solution, and furthest from the negative ideal solution. The sorting of the results of the sum of the distances, is the recommended solution. The distance referred to here is the Euclidean distance calculated from the position of the positive ideal solution, and the position of the ideal negative solution. This method is described by development [22].

For the cost criterion (where lower is better), then the r_{kj} performance rating is using equation (3).

$$r_{kj}(x) = \frac{x_j^- - x_{kj}}{x_j^- - x_j^*} \quad (3)$$

From the rating obtained on each criterion for each alternative, it can be calculated PIS (Positive Ideal Solution) and NIS (Negative Ideal Solution) using equation (4).

$$PIS = A^+ = \{v_1^+(x), v_2^+(x), \ldots, v_j^+(x), \ldots, v_m^+(x)\} \quad (4)$$

The next step is to calculate the Euclidean distance of each alternative, to PIS and NIS. This calculation is show in Equation (5) and Equation (6).

$$D_k^* = \sqrt{\sum_{j=1}^{m}\left[v_{kj}(x) - v_j^+(x)\right]^2},\ k = 1, \ldots, n \quad (5)$$

$$D_k^* = \sqrt{\sum_{j=1}^{m}\left[v_{kj}(x) - v_j^-(x)\right]^2},\ k = 1, \ldots, n \quad (6)$$

Confusion Matrix

Confusion Matrix or more commonly known as contingency table is a matrix that may be very large. In this matrix, a correct classification action is contained on the diagonal axis of the matrix. In other columns, the entire matrix is false. A genetic algorithm uses a set of rules to test the suitability of these rules to the problem at hand, its derivatives[23]. In this case the confusion matrix is used to assess the level of suitability of the classification process, in classifying a decision with the actual conditions. An example of a confusion matrix is show in table 1.

Table 1. Confusion Matrix Cost

	Classification As A	**Classification As B**
Actual Class A	0	1
Actual Class B	1	0

Then, in its use, each classification decision taken is compared with the actual class, to get the value of the cost of the decision. The calculation is done using Equation (7).

$$C = \sum_{i=1}^{m}\sum_{j=1}^{n} C_{ij} \quad (7)$$

C = total *cost*
i = classification decision index.
j = actual index.

RESEARCH METHODS

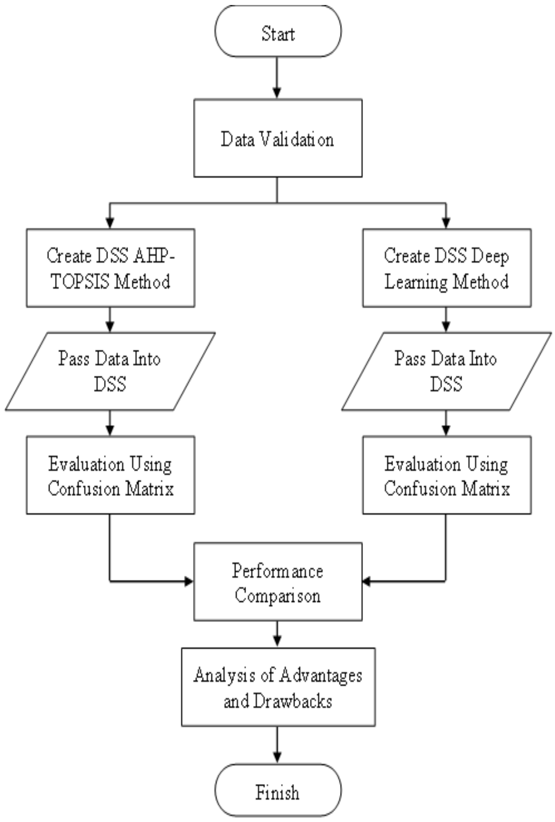

Fig 4. Flowchart of research stages

Testing Method

Metode AHP-TOPSIS

First, the normalization value is carried out, then for each criterion, a highest (ideal) and the lowest (negative ideal) value is determined from the existing set of alternatives. Then, each alternative will be calculated its Euclidean distance to the ideal solution, and added with its Euclidean distance to the ideal negative solution. The equations for calculating the Euclidean distance from the ideal solution and the ideal negative solution are show in equation (8) and equation (9).

$$S_i^+ = \left[\sum_{j=1}^{m}\left(V_{ij} - V_j^+\right)^2\right]^{\frac{1}{2}} \quad (8)$$

S = Euclidean distance
V = Performance normalized vector
i = Criteria
j = Alternative

$$S_i^- = \left[\sum_{j=1}^{m}\left(V_{ij} - V_j^+\right)^2\right]^{\frac{1}{2}} \quad (9)$$

S = Euclidean distance
V = Performance normalized vector
i = Criteria
j = Alternative

After obtaining the Euclidean distance from each positive ideal solution and negative ideal solution, then the final performance assessment is carried out, and in this case the final fitness. This calculation is performed using Equation (10).

$$P_i = \frac{S_i^-}{S_i^+ + S_i^-} \quad (10)$$

P_i = Final performance
S+ = Euclidean distance from positive solution
S- = Euclidean distance from negative solution

Metode Deep Learning

This model receives input data from the input layer, and then forwards it to the processing layers, or is called the hidden layer. The processing results will then be displayed as a value in the output section, where this value is a probability value, or recommendation, that a student is eligible to be proposed into a scholarship category. Calculations for each hidden layer will use neurons with a perceptron computational model, according to Equation (11). In this equation, there are i inputs for an output on the j perceptron.

$$y_j = f_a(w_{1,j}.x_1 + w_{2,j}.x_2 + \cdots + w_{i,j}x_i + b_j) \quad (11)$$

y : perceptron external element
x : perceptron input element
f_a : activation function
b : bias
w: weight
i: input index
j: output index
n: input index to n

After making this deep learning model, a training process will be carried out on the model. This training aims to change the parameters contained in the model, namely weight and bias in it. Changes to the parameters in this model will be based on the Stochastic Gradient Descent method, where the current parameter values will be entered into the cost function to determine updates to the parameters owned, to reduce the cost function. This cost function is show in Equation (12).

$$f_c(m,b) = \frac{1}{n}\sum_{i=1}^{n}(h_\theta(x_i) - y_i)^2 \quad (12)$$

f_c = cost function
m = weight
b = bias
n = the number of evaluation data, in this study using 32 data per batch
h_θ = prediction function with m and b as parameters
x_i = input data to i
y_i = output data to i

Based on the resulting cost, all the parameters contained in this deep learning model will be updated with the aim of reducing costs, which is expected to ultimately increase the accuracy of this model. However, to ensure that there is no overfitting of the model in training, a validation will be carried out, by separating the data that will be used for training, into 2 data sets. Data on previous year's scholarship recipients will be broken down in a ratio of 80-20. More data will be used to train the model, and less data will be used to perform validation tests, where deep learning models are validated by seeing how they perform against never before seen data sets.

RESULT AND DISCUSSION

DSS AHP-TOPSIS

One of the problems with this system's DSS is that it produces a recommended value compared to other values. This value does not have much meaning, when the desired output is a recommendation value in the form of 0 or 1. For this reason, it is necessary to create a threshold value, where all prospective scholarship recipients who have a value above this value are considered to have met the requirements to be recommended to receive a scholarship. and vice versa. Based on the data, the number of accepted students is as show in Table 2.

Table 2. Number of Scholarship Recipients Who Received Scholarships.

Num	Scheme	Number of Registrants	Number of Received
1	Merit	171	69
2	Bidikmisi	46	10
3	Independent	97	17

Based on this value, the decision to make a recommendation for a prospective scholarship recipient will be based on the value of the amount received. This means that the candidate for the scholarship recommended by the DSS is the candidate with the highest score as much as the total number of students received. The results of the evaluation are carried out by comparing the results of the recommendations by the DSS, with the data of the actual recipients. By taking n-number values, the highest score is accepted as a prediction recommended by DSS, and the rest as predictions are not recommended. Then the accuracy is calculated by comparing the number of correct predictions (according to the actual data of scholarship recipients) against all predictions made. From these calculations, the accuracy values are obtained as Table 3.

Table 3. Accuracy of DSS Recommendations on Actual Results

Num	Scheme	Prediction Accuracy
1	Prestasi	56.72 %
2	Bidikmisi	65.21 %
3	Mandiri	95.87 %

DSS Deep Learning

At this stage, the three models that have been made are carried out. Algorithm for optimization will use Adam's algorithm, while for loss calculation will use binary_crossentropy approach. In full, the training of the model is carried out using the training parameters as show in Table 4. Then conducted training on the model for prediction of scholarships. The training of the first model runs for 59 training epochs before the callback occurs. The results of the training are shown in Fig 5. It was found that the minimum loss value is 0.5017, with an accuracy value of 71.93%.

Table 4. Training Model Parameters

Num	Parameters	Value
1	Optimizer	Adam
2	Loss	Binary_crossentropy
3	Metrics	Binary_accuracy
4	Callbacks	Early Stopping

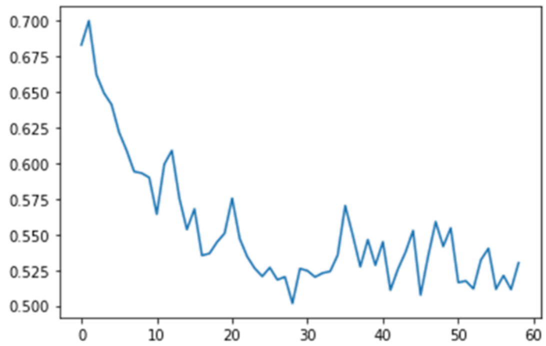

Fig 5. Graph of training loss value against training epochs

Then training was conducted on the model for prediction of the bidikmisi scholarship. The training of the second model runs for 35 training epochs before the callback occurs. The results of the training are shown in Fig 6. It was found that the minimum loss value is close to 0, with an accuracy value of 100%.

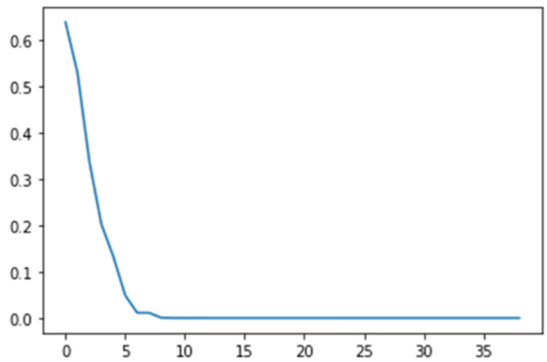

Fig 6. Graph of training loss value against training epochs

Then training was carried out on the model for predicting independent scholarship. The training for this third model runs for 43 training epochs before the callback occurs. The results of the training are shown in Fig 7. It was found that the loss value is minimal to close to 0, with an accuracy value of 100%.

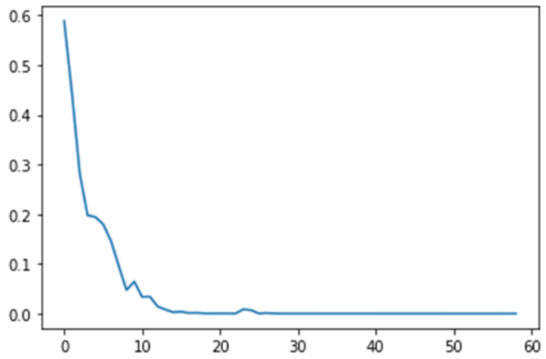

Fig 7. Graph of training loss value against training epochs

Research activities have been carried out, and accuracy performance results from both approaches have been found. The first approach utilizes calculations based on the AHP and TOPSIS approaches. The second approach utilizes a supervised learning approach based on deep learning. The results of both approaches are shown in Table 5.

Table 5. Performance Comparison of the Two Approaches

Num	**Scholarship Scheme**	**AHP-TOPSIS**	***Deep learning***
1	Merit	56.72 %	71.93 %
2	Bidikmisi	65.21 %	100 %
3	Independent	95.87 %	100 %

From the inspection of the results obtained, it can be concluded several things that might lead to these results. First, the AHP-TOPSIS method cannot consistently detect the effect of each criterion on the probability of selecting a candidate for a scholarship. This is mainly due to the limitations of AHP-TOPSIS in weighting each criterion. Second, the deep learning approach is large for limited input data, this allows the model to better learn the relationships between the criteria, but may also signal an overfitting of the deep learning model to the data used for learning. Third, there are limited data used for training and testing, so there is a possibility that the data will not represent the actual situation in the future.

CONCLUSION

The DSS model with the AHP-TOPSIS approach has been successfully created, with accuracy performance for the introduction of merit scholarship scheme data of 56.72%, bidikmisi scholarship data of 65.21%, and independent scholarship data of 95.87%. Meanwhile, the DSS model with a deep learning approach has been successfully created with accuracy performance which produces 71.93% achievement scholarship scheme data, 100% bidikmisi scholarship data, and 100% independent scholarship data.

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