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The Intelligent Decision System Based on Hybrid Decision Tree to Determine The Level of Lecturer Performance

I.G.P. Asto Buditjahjanto*, Andrian Pratama, and Muchlas Samani

Electrical Engineering, Universitas Negeri Surabaya, Indonesia
*e-mail: asto@unesa.ac.id
Post Graduate of Vocational Education, Universitas Negeri Surabaya, Indonesia
e-mail: andreatkpmks@gmail.com
Post Graduate of Vocational Education, Universitas Negeri Surabaya, Indonesia
e-mail: msamani@unesa.ac.id

Abstract

The performance of a higher education institution is determined by the performance of the lecturers. Lecturer performance is influenced by variables such as motivation, organizational culture, leadership, and continuous professional Development. Meanwhile, the level of lecturer performance is formed from variables such as education and teaching, research, community service, and lecturer support duties. This research aims to develop an intelligent decision system using a hybrid decision tree that is capable of determining the level of lecturers' performance in higher education. The research method used to form an intelligent decision system was formed in three stages. The first stage is to determine the levels of the number of lecturer performances using the elbow method, the second stage is to cluster the level of lecturer performance using the K-means method and the third stage is to determine the level of lecturer performance using the decision tree method. The research results obtained three levels of lecturer performance criteria namely Good, Sufficient, and Poor. The Intelligent Decision System that was built is capable of providing decisions with an accuracy level of 0.889 and a precision level of 0.888. The results obtained are significant enough to be used to determine the level of lecturer performance.

Keywords: *Decision Tree, Innovation, Intelligent Decision System, Performance, Technology*

1 Introduction

The borderless global era causes intense competition in higher education institutions. Higher education institutions are required to be able to provide the best service for their users such as students and the industrial world as users of college graduates. Higher education is a center for human resource development. To be able to develop human resources, lecturers are required to be able to provide the best and most up-to-date knowledge, skills, and expertise to their institutions. Lecturer performance can be performed such as the quality of teaching and education, the quality and quantity of research, the quality and quantity of community service, and the Lecturer Support Duties

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carried out. Increasing the research output of lecturers is critical to increasing teaching quality and institutional status [1]. One way to find out a lecturer's contribution to their institution is to measure the lecturer's performance. Lecturer performance is a never-ending topic in education, and statistics may be utilized to investigate it [2]. Several factors have an important influence on lecturer performance such as Continuous Professional Development (CPD), leadership, cultural organization, and motivation. The authors [3] reported that motivation can provide enthusiasm for lecturers to carry out research well if it is assisted by improving the lecturer's ability to write articles. CPD has an important role in the career development of lecturers who teach in STEM fields [4]. In learning at a Higher Education institution, leadership factors also influence student performance and satisfaction [5].

Research [2] used path analysis to determine the correlation value which shows the connection between the reward system, Lecturer Commitment, Participation in Decision Making, and Lecturer Satisfaction on lecturer performance. This research did not measure the level of lecturer performance. Research [6] examined the relationship between ability, compensation, working environment, and leadership in lecturer's performances using the SEM method. The research shows that these four factors have a significant effect on the lecturer's performance. This research is only limited to showing the relationship between factors and does not examine the level of the lecturer's performance. Research [7] researched lecturer performance related to the assessments given to their students. This research only provides recommendations so that the lecturer's performance cannot be measured and tested using precision or accuracy. The data taken is based on a survey of students by the students to the 5% top and 5% bottom-rated lecturers. This research only reports lecturer performance and does not measure the level of lecturer performance.

The level of lecturer performance can be affected by factors such as the quality of teaching and education, the quality and quantity of research, the quality and quantity of community service, and the lecturer support duties carried out. These factors at the lecturer performance level must be implemented proportionally. If one of the factors is not implemented well, it can affect the level of lecturer performance. By knowing the level of lecturer performance, it can provide suggestions for higher education leaders to improve their lecturers. Also, it can be a means for the lecturer concerned to improve their performance if the lecturer's performance level is still low and maintain it for lecturers with a high level of lecturer performance. Therefore, the problem of this research is how to create an IDS based on Decision Trees to be able to determine lecturer performance levels.

The weakness of previous research is that the accuracy and precision in determining the level of lecturer performance have not been measured, so it can be improved by using machine learning methods. Machine learning methods such as DT can determine the accuracy and correctness of a system being built. Existing research mostly uses questionnaires to collect data, which is then analyzed statistically. There has been no research that has built an IDS to measure lecturer performance levels using machine learning methods. The contribution of this research is in the form of an IDS based on DT, which can determine the level of lecturer performance. The correctness of determining the level can be determined by the accuracy and precision values.

Therefore, an Intelligent Decision System (IDS) is needed to be able to determine the level of lecturer performance. Input variables for lecturer performance include significant factors such as CPD, leadership, cultural organization, and motivation. The output variable is the level of lecturer performance which is formed from factors such as teaching and education, research, community service, and lecturer support tasks. IDS establishes the level of lecturer performance in the form of categories, for example Good, Sufficient, and Poor. The IDS that is built can provide quick and accurate decisions regarding the level of lecturer performance criteria. The IDS developed is a hybrid decision tree, which combines the Decision Tree (DT) with the elbow method and the K-means method in building the IDS.

The authors [8] state that IDS is a self-contained technique that does a thorough study of decision systems based on past insights and anticipates a new intelligent, driven system for intelligent decision-making for a specific situation. IDS with its advantages has been widely applied in the field of supply chain reconfiguration [9], in the medical field where it is used to detect disease with high accuracy [10], in the field of marketing to predict the success of direct sales marketing [11], in the energy sector to be able to predict the future trends Residential Energy Consumption and to use Renewable Energy Utilization as alternative energy [12].

There hasn't been much study on utilizing machine learning to create IDS for measuring the level of lecturer performance. The author [13] states that IDS is a combination of a Machine Learning-based intelligent system that aids in further optimization, makes critical decisions regarding plans or complicated issues without the need for human interaction, and expedites the process of making decisions that are more productive and effective. This research develops an IDS using a Decision Tree (DT) as Machine Learning for decision-making. DTs are machine learning algorithms that are adaptable and capable of handling both regression and classification problems. DTs are simply represented as a collection of logical rules that characterize the decision functions. When used for decision support, DTs offer concise justifications for specific decisions. Typically, these explanations take the form of a single logical rule that applies to the given situation and is made up of the conjunction of many understandable premises [14].

DT was chosen because it is easy to carry out computer simulations with faster time consumption if the number of nodes in the tree is not too large. Apart from that, DT has advantages such as: being easy to understand and interpret by humans because its shape is similar to a decision tree, handling data that is unstructured and not well labeled, handling data that has irrelevant or unimportant attributes, handling data that has missing or incomplete values. With its advantages, DT has been widely applied, such as in the energy sector to regulate a Hybrid PV/T Solar System's Efficiency [15], in the telecommunications network sector to help a manufacturing network allocate recently received orders [16], in the banking sector to predict the bankruptcy of a bank [17], and in the education sector to create a decision tree classifier for the thorough evaluation of PLOs that are directly correlated with computer programming-related CLOs [18] and can also use an assessment tool to see if the Vocational Education program participants are adequately equipped to use their egress skills in new emergencies in the same virtual environment. [19]. This research aims to develop an IDS to determine the level of lecturer's performance in higher education institutions.

2 Related Work

2.1 Performance Lecturer

Measuring or determining performance is very necessary to determine whether a system is working well or not. In the field of education, students need to measure their performance in the learning process to know each student's progress in learning in class [20]. As with lecturers, measuring or determining the performance of lecturers at higher education institutions is needed to be able to provide a benchmark or measure of the role and contribution of these lecturers toward the institution. The performance of lecturers can be measured through several factors, for example, research, teaching and education, and social service. Through research, we can find out how much research has been carried out and what its quality is. Good research is the performance of lecturers which has an impact on higher education performance [21].

On the other side, several factors can influence lecturer performance, for example, leadership, motivation, cultural organization, and CPD. According to [1], the position of the organizational leader is especially important in establishing the vision and mission of the research. Supported by [22] stated that many studies have been conducted to illustrate the importance and effect of leadership on lecturers' research productivity. The CPD factor is needed by lecturers to develop themselves so they can keep up with developments in their knowledge and careers. The Authors [23] stated that the development of appropriate CPD in polytechnic technical lecturers means that lecturers' competencies will also become more up-to-date and able to compete with other lecturers.

2.2 Intelligent Decision Support with Decision Tree

Nowadays, decision-making problems are increasingly complicated and complex. An intelligent system is needed that can help solve this problem. IDS as a form of machine learning has advantages in speed and accuracy in making decisions. IDS can provide support for its users to assist in determining complex decisions with a large number of inputs and is complicated with the accuracy of the decisions that must be given. IDS is used to build accurate and dynamic models of the process and to provide analytical views of the data [24]**.** DT is a type of machine learning that has simplicity and ease of use as a tool for decision-making [25]. In a decision support system, DT can be used to make clustering easier for high-speed streaming data can be transformed into operational intelligence efficiently[26]. DT is widely used because it has several advantages, such as being easy to understand and interpret by humans [27], capable of handling both numerical and categorical data [28], and can be used for classification [8].

3 The Proposed Method

This research focuses on higher education such as government-owned polytechnics. Therefore, the research population was lecturers at these polytechnics. The sample was taken using a purposive sampling technique by determining samples at five polytechnics, namely aviation polytechnic, shipping polytechnic, railway polytechnic, marine polytechnic, and agricultural development polytechnic. Sample collection was obtained by distributing questionnaires to lecturers at the 5 polytechnics. Questionnaires were distributed online and offline.

The factors such as motivation, the organizational culture variable, leadership, and CPD, are selected because they can influence lecturer performance according to the references [2], [3], [4], [5]. The selected factors are related to the indicators. Motivation factor with two indicators, namely intrinsic and extrinsic, organizational culture factor with five indicators, namely self-awareness, initiative, social relations, performance, and team orientation, the leadership factor with four indicators, namely instructive, consultative, participative, delegation, and the CPD factor with three indicators, namely independent professionalism development, social development of professionalism, formal professional development. These 14 indicators become input for IDS.

The object of this research is the factors that become input variables for building an IDS. These variables are factors that influence lecturer performance. The input variables are the motivation variable with two indicators, namely intrinsic and extrinsic, the organizational culture variable with five indicators, namely self-awareness, initiative, social relations, performance, and team orientation, the leadership variable with four indicators, namely instructive, consultative, participative, delegation, and the CPD variable with three indicators, namely independent professionalism development, social development of professionalism, formal professional development. These 14 indicators become input for IDS. Table 1 shows the input variables and indicators for the IDS.

Table 1: Variables and IDS input indicators

No	Indicators	Variables
1	Intrinsic	Motivation
2	Extrinsic	
3	Self-awareness	Organizational culture
4	Initiative	
5	Social relations	
6	Performance	
7	Team orientation	
8	Instructive	Leadership
9	Consultative	
10	Participative	
11	Delegation	
12	Independent professionalism development	Continuous Professional Development
13	Social development of professionalism	
14	Formal professional development	

The factors used to form and evaluate levels of lecturer performance consist of four indicators, such as education and teaching, research and science development, community service, and lecturer support duties. These four indicators are based on research [2] that showed each indicator has a good means matrix of the lecturer performance constructs with a score of 3.419 on a scale of five.

Table 2: Lecturer performance variables and indicators

Variable	Indicators
Level of Lecturer Performance	Education and Teaching
	Research and science development
	Community service
	Lecturer Support Duties

Table 2 shows the variables used to form levels of lecturer performance which consist of four indicators, such as education and teaching, research and science development, community service, and lecturer support duties. These four indicators become input to build levels of lecturer performance, while the output level of lecturer performance is built from the number of levels of clustering results using the Elbow method. Table 3 shows the four indicators with the number of levels and their criteria.

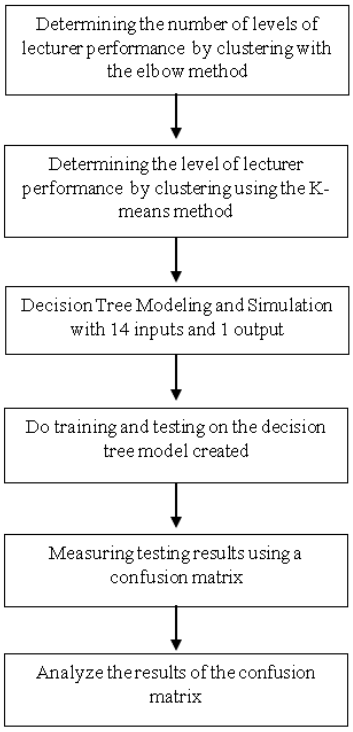

Fig. 1. Steps for creating an IDS to determine criteria and level of lecturer performance

Creating an IDS for measuring the level of lecturer performance consists of several steps as shown in Figure 1. The first step is to determine the optimum number of lecturer performance levels to be created. This stage is by selecting one indicator from the lecturer performance input, for example intrinsic, with the output indicator of lecturer performance, for example, education and teaching. The model system is 1 input with 1 output as seen in Figure 2. The Elbow method is used to determine the optimum number of clusters used as the number of lecturer performance levels. After obtaining some clusters for lecturer performance as the number of levels, the second step is to cluster the lecturer's performance using Kmeans so that clusters/levels are obtained for each combination of IDS input. The model system is 4 inputs with 1 output as shown in Table 3.

The next step, creating a Decision Tree model. The DT model is prepared with 14 input indicators as in Table 1 and 1 output of lecturer performance level as shown in Table 3. Training is carried out on the DT model created. Data amounting to 70% from 60 samples or 42 samples was used to train the DT model that was prepared. After obtaining a training accuracy score that follows the standards carried out, the next step is testing using 30% of 60 samples or a total of 18 samples. Next, analyze the testing results through a confusion matrix. If it meets the specified standards, then IDS can be used.

In the initial stages of IDS development, calculations were carried out to determine the optimal cluster number for determining the level of lecturer performance using the elbow method with the following algorithm:

1. Enter data on one of the lecturer's performance indicator

2. Initialize the number of clusters K

3. Perform clustering using the K-Means algorithm with K clusters

4. Calculate the SSE value

5. Save the SSE value

6. Repeat steps 3-5 for K = 1 until K = Kmax

7. Plot a graph of SSE versus number of clusters

8. Determine the elbow point on the graph

9. The optimal number of clusters is the number of clusters at the elbow point

10. Output the optimal number of clusters

Next, the results of determining the optimal number of lecturer performance levels are used to form a DT model with 14 inputs and 1 decision output. The DT algorithm is as follows:

1. Enter data 14 indicators as input and 1 output of level lecturer performance

2. Separate 70% of the data into training data and 30 % of the data into test data

3. Perform data preprocessing

4. Create a Decision Tree model:

a. Select the best attribute as the root node

b. Divide the data into subsets based on the attribute values

c. Repeat steps a and b for each data subset until it reaches the stop condition

5. Perform pruning on the Decision Tree model

6. Evaluate the Decision Tree model using test data

7. If the evaluation results are satisfactory, use the Decision Tree model to predict new data

8. Decision Tree model output

4 Results

The results of distributing questionnaires to five government-owned polytechnics obtained 60 samples as data. The statistical description of the 60 samples is shown in Table 3. The highest mean score for the indicator is a performance indicator with a score of 3.333, and the lowest mean score is a research and science development indicator with a score of 1.719.

The samples were used to build the IDS. The IDS built consists of Hybrid DT which includes determining the number of criteria and levels of lecturer performance, forming criteria and level of lecturer performance, and classification to determine the criteria and level of lecturer performance.

Table 3: The statistical description of the data

No	Indicators	Mean	Std
1	Intrinsic	2.936	0.393
2	Extrinsic	2.976	0.480
3	Self-awareness	3.133	0.412
4	Initiative	3.233	0.435
5	Social relations	3.291	0.432
6	Performance	3.333	0.433
7	Team orientation	3.340	0.400
8	Instructive	2.633	0.445

9	Consultative	3.099	0.549
10	Participative	2.933	0.516
11	Delegative	3.008	0.457
12	Independent professionalism development	3.08	0.408
13	Social development of professionalism	3.306	0.399
14	Formal professional development	3.039	0.537
15	Education and Teaching	2.946	0.280
16	Research and science development	1.719	0.428
17	Community service	2.2	0.381
18	Lecturer Support Duties	1.739	0.390

4.1 Determining the number of criteria and levels of lecturer performance

The initial stage of this research was determining the number of clusters. The number of clusters was used to determine the number of criteria and levels of lecturer performance. The elbow method was used to determine the number of clusters. The input used for the cluster was Intrinsic indicators and education and teaching indicators. The simulation results obtained three clusters as shown in Figure 2, where elbows showed in number three for the number of clusters.

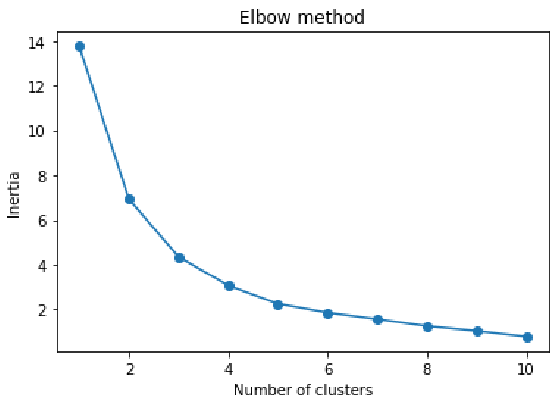

Fig. 2. Determination of the number of clusters

Table 4 shows the level and criteria of lecturer performance. Level 1 with poor criteria, level 2 with Sufficient criteria, and level 3 with good criteria.

Table 4: Level and criteria of lecturer performance

	Level	Criteria
Lecturer Performance	1	Poor
	2	Sufficient
	3	Good

4.2 Establishing criteria and level of lecturer performance

After knowing the optimum number of levels using the Elbow method, the next step is to determine each level and criteria from the 60 data from the 4 indicators of lecturer performance using the K-Means method. Determining the level of each respondent using

60 samples with several clusters of 3. The results of this clustering become output for IDS. Table 5 shows the results of lecturer performance level and criteria using K-Means.

Table 5: Clustering results of lecturer performance levels

Respondent	Education	Research	Community Service	Support	Cluster/Level
1	3.4	2.2	2.0	1.6	1
2	3.0	2.0	2.0	1.8	2
3	3.0	1.8	2.3	1.6	2
4	2.6	1.8	2.0	1.6	2
5	3.2	1.6	1.8	1.4	3
6	3.2	1.2	2.5	1.6	3
.	.	.	.	.	.
.	.	.	.	.	.
60	2.4	1.8	2.5	2.2	2

4.3 Classification to determine the criteria and level of lecturer performance

IDS is built by compiling a DT with 14 inputs and 1 output. The 14 inputs come from Table 1 and the lecturer performance levels come from Table 4. The distribution of classes for lecturer performance levels from the 60 samples is as follows: Level 1 is 14, Level 2 is 38, and Level 3 is 8 as seen in Figure 3.

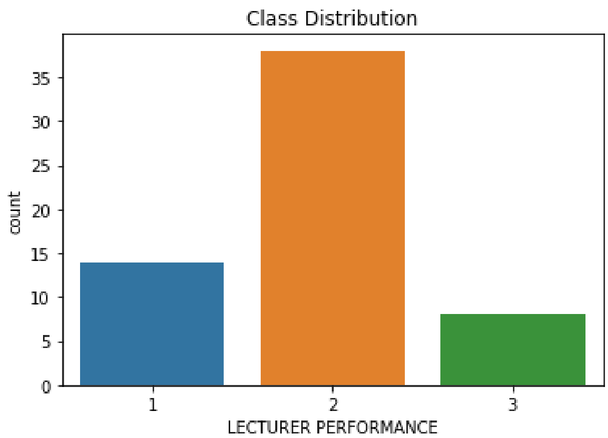

Fig. 3. The distribution of classes for lecturer performance levels

Criteria such as accuracy, precision, recall, and F-measure can be applied to performance evaluation to determine which classification algorithm performs the best. The following is the equation used to figure out the metric value [29].

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1 = \frac{2*Precision*Recall}{Precision+Recall} \quad (4)$$

True Positive (TP) occurs when the model predicts a positive result correctly. This indicates that the model produced a positive prediction, and the prediction proved true. False Positive (FP) occurs when the model predicts positive outcomes incorrectly. Consider it further, the model predicts the positive, while the reality is the negative. False Negative (FN) occurs when the model predicts an instance negatively. In other words, although the model predicts a negative outcome, the actuality is the best outcome. True Negative (TN) occurs when a negative instance is accurately predicted by the model. In other words, the model produced a negative prediction, and it proved correct.

This research used Spyder (Python 3.9) with the following parameter settings: The dataset shape is (60, 15), with a sample of 60 and 15 indicators consisting of 14 inputs and 1 output. test_size = 0.3, and random_state = 1 are the parameter settings for training and testing. The size of the testing sample data is 30%, and the training sample data is 70%. In each testing and training, a random state of 1 is used.

Training is carried out to train DT. Training data used 70% of the total 60 samples or 42 samples. The training results showed that the accuracy value obtained is 1.0. After obtaining a training accuracy score that meets the standards, the next step is testing using 30% of the total 60 samples or 18 samples. The testing results show that the accuracy value obtained is 0.889, the precision value is 0.888, the recall is 0.939 and the F1 Score is 0.9. Figure 4 is a Confusion Matrix for the classification of Lecturer Performance levels from testing results. In the actual label, there are 4 labels 0 (Level 1), 11 labels 1, and 3 labels 2. Meanwhile, for the predicted label, there are 6 labels 0 (Level 1), 9 labels 1 and 3 labels 2. There is a difference between the actual label and predicted label on label 0 and label 1, while label 2 has the same number.

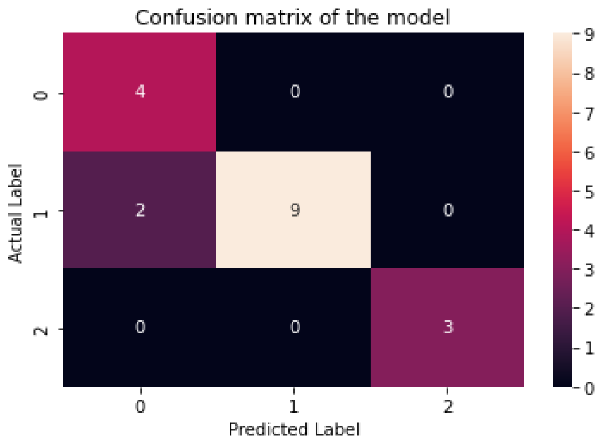

Fig. 4. Confusion Matrix for Classification of Lecturer Performance Levels

The results of running DT testing show the classification results as shown in Table 6. The precision column at level 1 has a value of 0.67 while level 2 and level 3 have a precision value of 1. The support column shows that the test data for level 1 is 4, level 2 is 14, and level 3 is 3.

Table 6: Classification report

Level	Precision	Recall	F1-Score	Support
1	0.67	1.00	0.80	4
2	1.00	0.82	0.90	11
3	1.00	1.00	1.00	3

5 Discussions

The main result of the research is an IDS which can classify and determine the level of lecturer performance. IDS which was built using hybrid DT is used to determine the number of lecturer performance levels, determine lecturer performance levels, and classify lecturer performance. The IDS test results show good accuracy and precision values so that it can classify and determine lecturer performance levels.

There were unsatisfactory research results, specifically the training results showed an accuracy value of 1. However, when testing was carried out, the accuracy value was only 0.889. Another unsatisfactory research result is regarding precision. The overall precision testing results were 0.888. However, there was an unexpected result, namely that the precision value for determining level 1 was only 0.67, while for determining level 2 and level 3 it was in line with expectations, namely 1. These results are shown in Table 6.

Table 7 shows the performance comparison results of several classification methods such as Hybrid DT, SVM, KNN, and Naïve Bayes using this research data. The comparison results show that the performance of Hybrid DT in the aspects of Accuracy, Precision, Recall, and F1-Score has a better score than other classification methods except that SVM precision is superior. These results are supported by [30] who used MWMOTE to assess the classification techniques of Decision Tree, K-NN, Naive Bayes, and Support Vector Machine (SVM) on imbalanced data. The outcomes showed that, for balanced data with MWMOTE, the Decision Tree outperformed K-NN, Naive Bayes, and SVM in terms of recall, precision, F-measure, and accuracy.

Surveys and analysis comparing the three data mining classification algorithms (Bayesian, KNN, and Decision Tree) reveal that all Decision Tree techniques are simpler, more accurate, and have lower error rates than K-NN and Bayesian algorithms [31].

Different results were shown by the author [32] stating that different test datasets can influence the performance evaluation results of each type of classifier method. His research states that Naïve Bayes provides better results compared to other classifier methods. The author [33] stated that for research with large databases for an energy simulation tool, the results showed that Naive Bayes exhibited high accuracy compared to Decision Tree, and k-Nearest Neighbor in searching alternative designs.

Table 7: Comparison of performance Evaluation in determining Lecturer Performance Levels

Classification Methods	Accuracy	Precision	Recall	F1-Score
Hybrid DT	0.88	0.88	0.93	0.90
SVM	0.83	0.93	0.69	0.75
KNN	0.66	0.62	0.55	0.57
Naïve Bayes	0.58	0.46	0.54	0.48

IDS based on hybrid DT still has shortcomings, including accuracy and precision values that are not yet optimal. The causes could be unequal class distribution. The level variation for 60 samples is not balanced enough. It is known that level 1 is 14, level 2 is 38, and level 3 is 8, so when testing is carried out using 18 samples or 30% of the total data, the number of level variations becomes smaller, namely, level 1 is 4, level 2 is 11. and level 3 as many as 3 pieces. Therefore, the accuracy and precision for determining level 1 is not very good.

The limitation of this research is that the accuracy value is still 0.88. Therefore, improvements are needed, both adding sample data and balancing the number of samples for each class, so that the accuracy of DT in determining lecturer performance levels can increase. In general, IDS using hybrid DT can be used to determine lecturer performance levels.

6 Conclusion

The IDS which is prepared by combining determining the number of levels using the elbow method, leveling lecturer performance using Kmeans, and determining levels using DT can determine the level of lecturer performance. This IDS can work well and can provide the right decision to determine the level. In the future, improvements are needed to increase accuracy and precision by updating the IDS and adding larger data samples. The implications of this research can be used to help Higher Education develop the performance of lecturers in their environment.

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Notes on contributors

I.G.P. Asto Buditjahjanto received his Ph.D. degree in game technology from Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia. He is currently a lecturer at the Universitas Negeri Surabaya, Indonesia. His research interests include optimization, intelligent systems, computational intelligence, and machine learning

Andrian Pratama is pursuing his Ph.D. degree in vocational education in Universitas Negeri Surabaya, Indonesia. His research interests include organizational management, vocational education, and educational management

Muchlas Samani received his Ph.D. degree in evaluation education from IKIP Jakarta, Indonesia. He is currently a professor at the Universitas Negeri Surabaya, Indonesia. His research interests organizational management, vocational education, and educational management.