Mathematical Modelling of Engineering Problems
Vol. 10, No. 1, February, 2023, pp. 220-226
Journal homepage: http://iieta.org/journals/mmep

Measurement and Prediction of Effect Slenderness Ratios and Aggregate to the Compressive Strength of Concrete by the Core-Drilling Method in Tandem with Machine Learning

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https://doi.org/10.18280/mmep.100125

Received: 24 October 2022
Accepted: 20 January 2023

Keywords:
high strength concrete, compressive strength, drilled cores, machine learning

ABSTRACT

The slenderness ratio, length to diameter, of the cylindrical concrete samples of the slab block by the core-drilling method is believed to affect the compressive strength other than the aggregates in the concrete. In this study, the relationship between the compressive strength with mixing and slenderness ratio of cylindrical concrete specimens was investigated by statistics. Further, the discrimination model for mixing cylindrical concrete specimens has been developed by using machine learning algorithms, including support vector machine (SVM), linear discriminant analysis (LDA), k-nearest neighbor (k-NN), and random forest (RF). A total of 180 cylindrical concrete specimens have been measured for compressive strength using UTM. The sample consisted of a mixture of type-A and type-B with a slenderness ratio of 2.48, 2.72, and 3.28, respectively. Samples were obtained by the core-drilling method from slab block concrete. The ANOVA tests showed that the aggregate and slenderness ratio caused a significant difference in the compressive strength of the concrete ($p<0.05$). This indicates that the type of aggregate mixture in concrete and the slenderness ratio of cylindrical concrete specimens significantly affect the compressive strength of the concrete. The model for discrimination of mixing cylindrical concrete specimens using machine learning algorithms can be used with satisfactory results. LDA is a machine learning algorithm that can show stability in the training and testing stages with accuracy reaching 78% and inconsistency of less than 2.63% (the smallest compared to others). The descending order of machine learning algorithms based on their consistency is LDA > RF > SVM > k-NN. Subsequently, this model can discriminate the aggregate mixture on cylindrical concrete specimens obtained from the core-drilling method.

1. INTRODUCTION

Drilling and testing concrete cores is a popular method of measuring the in-situ strength of the material. Despite the method's costly and time-consuming activities, they produce accurate and relevant findings since cores are mechanically tested to failure. The test findings should be carefully evaluated, as core strengths depend on various variables, including the specimen's diameter, length, slenderness ratio, aggregate mixing, drilling direction, and reinforcing steel bars [1-3]. The core's diameter is crucial when analyzing the results of core strength tests. As long as the core diameter is three times greater than the maximum aggregate size in the concrete mixture, ASTM and British Standards recommend a minimum core diameter of 100 mm [4]. Turkish Standard permits the use of cores with a diameter of 50 mm [5]. But the Standard does not provide any adjustment factors to translate the strength of 50 mm cores to that of cores with bigger diameters.

Small-diameter cores are typically favored because they are simpler to drill, handle, and store than larger cores. In the case of small-diameter cores, the chance of cutting reinforcing bars is reduced during drilling, and a smaller hole is left for subsequent repair [6, 7]. Additionally, a more extensive region may be investigated because it is possible to get a lot of tiny cores. Furthermore, small-diameter cores could be the sole option in some circumstances when conventional core specimens with a slenderness ratio of 2 are sought. Even with a slenderness ratio of 1, it is often hard to get 100 mm diameter cores in structural reinforced concrete components, particularly in pre-stressed units. This can be a result of member dimension restrictions or crucial reinforcement places.

Small-diameter cores are frequently criticized for being unreliable. There are conflicting findings regarding the relationship between core diameter and core strength; some researchers claim no association, while others claim that the strength of tiny cores is significantly lower than that of bigger cores [8-10]. The size of the specimen, cutting damage, and the connection between the maximum aggregate size and the core's diameter are the main elements that might lead to behavioral variations between small and big cores. Smaller cores are more likely to sustain damage when drilled, handled, and stored. With smaller cores, drilling damage may significantly impact measured strength because the ratio of cut surface area to volume rises as core diameter drops. The aggregate's relative size to core diameter is significant for small-diameter cores. The impact of any aggregate freed by cutting will be amplified when the aggregate particles are substantial in comparison to the size of the core. Additionally, the test specimen's homogeneity of the material is far lower than it would be in a more significant specimen, which might affect the interior failure characteristics.

Concrete's compressive strength is frequently employed as a critical factor in the mix design process. However, the tests for compressive strength require time. Additionally, tests are often conducted seven and twenty-eight days after the concrete is poured into a form at a building site [11-13]. It is impractical to make corrections even if the results do not exceed the design's compressive strength. Because of this, it is crucial to estimate the strength of the concrete accurately and realistically before it is cast. In some structural circumstances, the strength of the concrete must also be assessed after the concrete has been exposed to various climatic conditions over a lengthy period.

Currently, various techniques are utilized to calculate in-situ strength, and each one offers a variety of advantages, including economy, avoiding delays in computing strength, etc. However, many of these methods allow for introducing all the elements that influence appropriate evaluation. In addition, the conceptual design, as well as non-invasive measurement, is crucial for processing these data, especially in the current engineering scope [14-19]. Therefore, involving machine learning in the analysis is a crucial thing to consider.

Several previous studies focused on estimating compressive strength by knowing the composition of the concrete [20-22]. However, no one has thought to focus on how to discriminate concrete composition if its compressive strength is known. This will be very helpful in the practical practice of determining the quality of concrete in the case of forensic analysis. Furthermore, the development of this model will be able to measure and estimate the aggregates used in the case of non-conformities in the field.

In this experimental investigation, the effects of aggregate type, as well as the slenderness ratio of the core upon the compressive strength, were studied. The correlations between compressive strengths and slenderness ratio from cylinder concrete were also confirmed. Finally, a model to discriminate against aggregates contained in cylinder concrete was developed using machine learning.

2. MATERIAL AND METHOD

The material consists of two types, namely mixing type-A and mixing type-B. Mixing type-A is to use the type of aggregate 1-2. Mixing type-B uses 1-2 aggregates combined with 2-3 aggregates. Both mixing types are combined with complementary concrete paste, cement, sand, and water. The ratio of cement and sand follows the Indonesian National Standard for Mixture selection procedures for normal concrete, heavy and mass concrete (SNI 7656:2012), which is 1:2, respectively. The physical properties of each aggregate in this study are presented in Table 1. The physical properties of aggregate for concrete used in this study follow the threshold for aggregate requirements for concrete in Indonesia for the slurry content of aggregate 1-2, which must be less than 1%, and aggregate of 2-3 must be less than 5%. In addition, the abrasion on the aggregate must be less than 50%.

Two concrete slab blocks are prepared according to standards according to the two types of aggregate mixing to be studied (type-A and type-B). After reaching concrete maturity (28 days) [23, 24], cylindrical concrete specimens were taken using the core-drilling method with diameters of 7.62 cm, 10.13 cm, and 12.7 cm, respectively (Figure 1). This difference in diameter samples aims to obtain a variation of the slenderness ratio of the concrete for further testing of its compressive strength. For each of these diameters, thickness variations were carried out, including 25.02 cm, 25.16 cm, and 34.56 cm. From the diameter and length of the sample, the slenderness ratio for cylindrical concrete specimens is 2.48, 2.72, and 3.28. A total of 30 concrete specimens from each treatment condition were prepared for testing. From that, 180 total cylindrical concrete specimens were studied in this study.

Table 1. Physical properties aggregate used in this study

Properties	Aggregate 1-2	Aggregate 2-3	Fine aggregate
Bulk density ($gr.cm^{-3}$)	1.34	1.33	1.30
Saturated surface dry	2.7 (0.92%)	2.7 (0.94%)	2.59 (1.08%)
Sludge waste (%)	0.57	0.48	2.11
Abrasion value (%)		19.19	
Slump test (cm)		10±2.0	

Figure 1. Cylindrical concrete specimens and slab block concrete

The compressive strength test from cylindrical concrete specimens was then carried out using electro-hydraulic servo universal testing machines (UTM HT-9501 series) (Figure 2). The primary parameter obtained from the electro-hydraulic servo universal testing machine is a graph between the x-axis of a time and the y-axis of a response in the form of compressive strength in MPa units. Furthermore, the maximum compressive strength point of the graph is further analyzed. The maximum compressive strength is recorded in MPa. Cylindrical concrete specimens are placed between the lower plates centrically, and loading is carried out at a speed of 4-6 $kg.s^{-1}.cm^{-2}$.

Figure 2. Compressive strength data acquisition using UTM

Statistical data analysis was performed using analysis of variance (ANOVA). The general steps of ANOVA include setting up the null and alternative hypotheses, determining the appropriate ANOVA test to use (e.g. one-way or two-way), checking assumptions (normality and equal variances), and interpreting the results. Specific processes in ANOVA include calculating the sum of squares, degrees of freedom, mean squares, and F-statistic to determine the statistical significance of the differences between group means. This is conducted to observe the significance of the effect of the level of treatment on the dependent variable [25]. The confidence level applied is 95%. In addition, if there is a difference between treatments on the compressive strength value at that confidence level, proceed with the Duncan test.

The prediction made in this study is a qualitative model by applying discrimination to distinguish the type of aggregate tendency used in cylindrical concrete specimens. Machine learning algorithm with the supervised type used in this study includes support vector machine (SVM), linear discriminant analysis (LDA), k-nearest neighbor (k-NN), and random forest (RF). Machine learning algorithms are executed using python code by utilizing packets from scikit-learn.

In addition, "gridsearchcv" from scikit-learn is also used optimally to optimize each algorithm's hyperparameters to discriminate the model. For SVM, hyperparameters that can be optimized, including C coefficient, kernel, gamma, independent term in the polynomial kernel, shrinking, decision function shape, tolerance for stopping criterion, the maximum number of iterations, and boolean parameter to enable probability estimates [26]. For LDA, hyperparameters that can be optimized, including solver, shrinkage, priors, store covariance, tolerance for stopping criterion, number of components to keep, and a method used to estimate the covariance matrix [27]. For k-NN, hyperparameters can be optimized, including several nearest neighbors, distance metric, weighting, leaf size, the algorithm used to find the nearest neighbors, power parameter for the Minkowski distance metric, and several parallel jobs to run for neighbors search [28]. For RF, hyperparameters that can be optimized, including a number of decision trees in the forest, a function used to measure the quality of a split, the maximum depth of the decision trees, a minimum number of samples required to split an internal node, a minimum number of samples required to be at a leaf node, number of features to consider when looking for the best split, bootstrap, boolean parameter that controls whether or not to use out-of-bag samples to estimate the generalization accuracy, number of jobs to run in parallel for both fit and predict and seed used by the random number generator [29].

In the development stage of the discrimination model (Y) to be able to distinguish the type of aggregate tendency used in cylindrical concrete specimens, independent variables (X) are used, including diameter (x_1) and length (x_2) of cylindrical concrete specimens, slenderness ratio (x_3) and compressive strength of concrete (x_4). Every variable in this study indeed correlates. Still, the direction of the correlation is not known with certainty. Hence, using a machine learning algorithm that works without knowing the relationships in the independent variables is very appropriate in this case.

The data was split randomly from the total dataset of 180 testing samples, with a proportion of 80% for training and 20% for testing. The model's performance is measured using a confusion matrix focusing on accuracy, precision, sensitivity (recall), and F1-score. Based on these parameters, the best model is then determined to discriminate the tendency of aggregates used in cylindrical concrete specimens by computation at the stability of each parameter in the training and testing stages of the tested dataset.

3. RESULT AND ANALYSIS

3.1 Effect of mixing and slenderness ratio of cylindrical concrete specimens on compressive strength of concrete

The ANOVA of the effect of aggregate and the slenderness ratio on the compressive strength of cylindrical concrete specimens is presented in Table 2. It can be seen that the aggregate composition of cylindrical concrete specimens significantly affects the compressive strength significantly ($p<0.05$). Besides, the slenderness ratio of cylindrical concrete specimens also significantly affects compressive strength at a p-value of 95%. However, the influence of both at the same time did not have a significant effect ($p>0.05$). The results of further tests using Duncan test showed that the average compressive strength of concrete type-A and type-B was significantly different for all types of slenderness ratio levels (Figure 3). Only in the condition of the slenderness ratio 3.28 and 2.48 there was no significant difference in compressive strength. This is probably because in the slenderness ratio of 3.28 and 2.48, the thickness of cylindrical concrete specimens tends to be the same (25.02 cm and 25.16 cm) with the difference in diameter (7.62 cm and 10.16 cm). However, cylindrical concrete specimens at a slenderness ratio of 2.72 use a thickness and diameter of 34.22 cm, 12.7 cm, respectively. This is in line with the research results of Gao et al. [30], who reported a positive relationship between the slenderness ratio and compressive strength.

3.2 Discrimination of mixing cylindrical concrete specimens using machine learning algorithms

The confusion matrix for the application of machine learning with the Support Vector Machine (SVM) algorithm is shown in Figure 4. The optimal parameter is achieved with penalty factor (C) of 1, the polynomial type kernel type polynomial with kernel coefficient (γ) is auto, the degree of the polynomial kernel function is two, and the independent in kernel function is 0.01. The SVM algorithm can generally discriminate cylindrical concrete specimens type-A on true positive (TP) and type-B on the true negative (TN) training phases of 53 and 59, respectively. In the testing phase, the SVM algorithm can discriminate cylindrical concrete specimens type-A on true positive (TP) and type-B on the true negative (TN) in training stages 9 and 14, respectively.

Table 2. ANOVA from effect of aggregate and slenderness ratio on compressive strength of cylindrical concrete specimens

Source of variation	Sum of square	df	Mean square	F	P-value
Aggregate	937.90	1	937.90	79.92	0.000
Slenderness ratio	3162.78	2	1581.39	134.75	0.000
Interaction	56.27	2	28.14	2.40	0.094
Within	2042.09	174	11.74		
Total	6199.04	179			

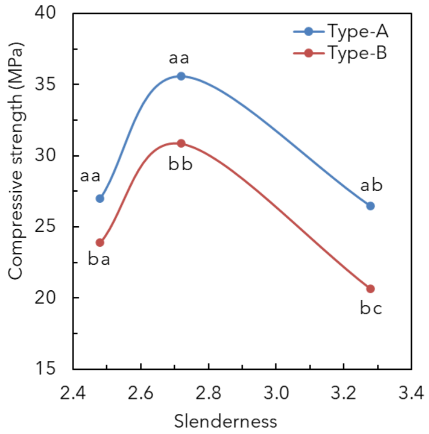
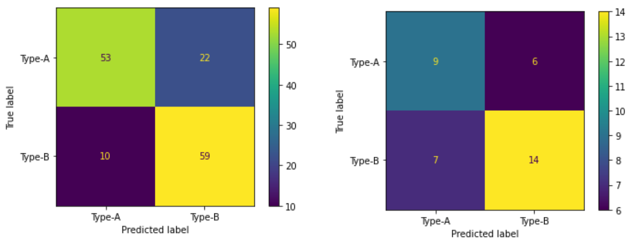


Figure 3. Relationship between slenderness vs. compressive strength



Training Testing

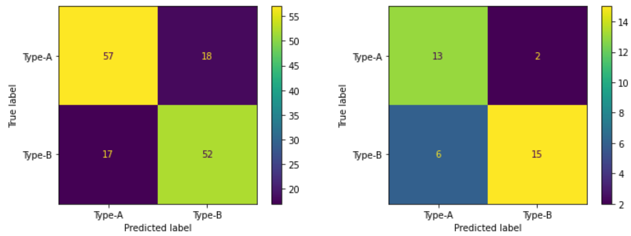
Figure 4. confusion matrix discriminates mixing aggregate of cylindrical concrete specimens using the SVM algorithm

The performance of the model in discriminating the mixing of cylindrical concrete specimens is presented in Table 3. The disparity in the accuracy of the model in discriminating aggregates in cylindrical concrete specimens in training and testing is 17.95%. Accuracy is the number of classifications a model correctly predicts divided by the total number of predictions made. The disparity in model precision in discriminating type-A and type-B aggregates on cylindrical concrete specimens in training and testing is 33.33% and 4.11%, respectively. Precision evaluates the fraction of correctly classified instances or samples among those classified as positives. The difference in sensitivity (recall) of the model in discriminating type-A and type-B aggregates on cylindrical concrete specimens during training and testing is 15.49% and 22.09%, respectively. Sensitivity is how sensitive the classification algorithm is to the attributes of the true positive. The disparity in the F1-score model in discriminating type-A and type-B aggregates on cylindrical concrete specimens in training and testing is 24.68% and 13.92%, respectively. F1-score is the harmonic mean of precision and recall and is a better measure than accuracy.

Table 3. Performance of SVM algorithms in discriminating mixing aggregate of cylindrical concrete specimens

Stage	Parameter	Type-A	Type-B
Training	Precision	0.84	0.73
	Recall	0.71	0.86
	F1-scores	0.77	0.79
	Accuracy	**0.78**	
Testing	Precision	0.56	0.70
	Recall	0.60	0.67
	F1-scores	0.58	0.68
	Accuracy	**0.64**	

The confusion matrix for the application of machine learning with the linear discriminant analysis (LDA) algorithm is shown in Figure 5. The optimal parameter is achieved by the composition of the solver using singular value decomposition (svd) with a number of components for the reduction in dimensionality being one. In general, the LDA algorithm can distinguish cylindrical concrete specimens type-A on true positive (TP) and type-B on the true negative (TN) training phases of 57 and 52, respectively. In the testing phase, the SVM algorithm can discriminate cylindrical concrete specimens type-A in true positive (TP) and type-B on the true negative (TN) in training stages 13 and 15, respectively.



Training Testing

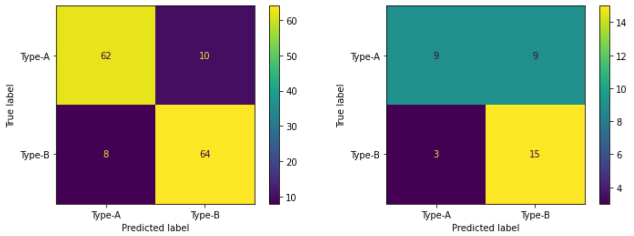
Figure 5. Confusion matrix discriminates mixing aggregate of cylindrical concrete specimens using the LDA algorithm

The performance of the model in discriminating the mixing of cylindrical concrete specimens is presented in Table 4. The disparity in the accuracy of the model in discriminating aggregates in cylindrical concrete specimens in training and testing is 2.63%. The disparity in model precision in discriminating type-A and type-B aggregates on cylindrical concrete specimens in training and testing is 11.69% and 18.92%, respectively. The difference in model recall in discriminating type-A and type-B aggregates on cylindrical concrete specimens during training and testing is 14.47% and 5.33%, respectively. The disparity in the F1-score model in discriminating type-A and type-B aggregates on cylindrical concrete specimens in training and testing is 1.30% and 5.33%, respectively. These results represent that the performance of the LDA algorithm is more stable than the SVM algorithm in discriminating the mixing aggregate of cylindrical concrete specimens.

Table 4. Performance of LDA algorithms in discriminating mixing aggregate of cylindrical concrete specimens

Stage	Parameter	Type-A	Type-B
Training	Precision	0.77	0.74
	Recall	0.76	0.75
	F1-scores	0.77	0.75
	Accuracy	**0.76**	
Testing	Precision	0.68	0.88
	Recall	0.87	0.71
	F1-scores	0.76	0.79
	Accuracy	**0.78**	

The confusion matrix for the application of machine learning with the k-nearest neighbor (k-NN) algorithm is shown in Figure 6. The optimal parameter is performed by using a k-number of neighbors is three. In general, the k-NN algorithm can distinguish cylindrical concrete specimens type-A on true positive (TP) and type-B on the true negative (TN) training phases of 62 and 64, respectively. In the testing phase, the k-NN algorithm can discriminate cylindrical concrete specimens type-A on true positive (TP) and type-B on the true negative (TN) in training stages 9 and 15, respectively.



Training Testing

Figure 6. Confusion matrix discriminates mixing aggregate of cylindrical concrete specimens using the k-NN algorithm

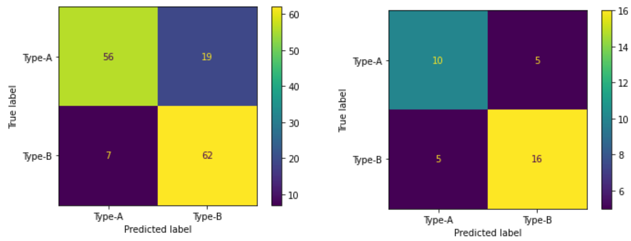
The performance of the model in discriminating the mixing of cylindrical concrete specimens is presented in Table 5. The disparity in the accuracy of the model in discriminating aggregates in cylindrical concrete specimens in training and testing is 23.86%. The disparity in model precision in discriminating type-A and type-B aggregates on cylindrical concrete specimens in training and testing is 15.73% and 27.91%, respectively. The difference in model recall in discriminating type-A and type-B aggregates on cylindrical concrete specimens during training and testing is 41.86% and 6.74%, respectively. The disparity in the F1-score model in discriminating type-A and type-B aggregates on cylindrical concrete specimens in training and testing is 31.03% and 19.32%, respectively. These results represent that the performance of the k-NN algorithm is not steadier than the LDA algorithm in discriminating the mixing aggregate of cylindrical concrete specimens.

The confusion matrix for the application of machine learning with the random forest algorithm is shown in Figure 7. Optimum parameters are achieved using the function to measure the quality of a split, namely, entropy, maximum depth of the tree is 15, minimum number of samples required to split an internal node is 3, minimum weighted fraction of the sum total of weights required to be at a leaf node is 0.1 and number of trees in the forest is 40. In general, the random forest algorithm can distinguish cylindrical concrete specimens type-A on true positive (TP) and type-B on the true negative (TN) training phases 56 and 62, respectively. In the testing phase, the random forest algorithm can discriminate cylindrical concrete specimens type -A on true positive (TP) and type-B on the true negative (TN) in training stages 10 and 16, respectively.

Table 5. Performance of k-NN algorithms in discriminating mixing aggregate of cylindrical concrete specimens

Stage	Parameter	Type-A	Type-B
Training	Precision	0.89	0.86
	Recall	0.86	0.89
	F1-scores	0.87	0.88
	Accuracy	**0.88**	
Testing	Precision	0.75	0.62
	Recall	0.50	0.83
	F1-scores	0.60	0.71
	Accuracy	**0.67**	

The performance of the model in discriminating the mixing of cylindrical concrete specimens is presented in Table 6. The disparity in the accuracy of the model in discriminating aggregates in cylindrical concrete specimens in training and testing is 12.20%. The disparity in model precision in discriminating type-A and type-B aggregates on cylindrical concrete specimens in training and testing is 24.72% and 1.30%, respectively. The difference in model recall in discriminating type-A and type-B aggregates on cylindrical concrete specimens during training and testing is 10.67% and 15.56%, respectively. The disparity in the F1-score model in discriminating type-A and type-B aggregates on cylindrical concrete specimens in training and testing is 17.28% and 8.43%, respectively. These results represent that the performance of the random forest algorithm is more stable than the k-NN algorithm in discriminating the mixing aggregate of cylindrical concrete specimens.



Training Testing

Figure 7. Confusion matrix discriminates mixing aggregate of cylindrical concrete specimens using the random forest algorithm

Table 6. Performance of random forest algorithms in discriminating mixing aggregate of cylindrical concrete specimens

Stage	Parameter	Type-A	Type-B
Training	Precision	0.89	0.77
	Recall	0.75	0.90
	F1-scores	0.81	0.83
	Accuracy	**0.82**	
Testing	Precision	0.67	0.76
	Recall	0.67	0.76
	F1-scores	0.67	0.76
	Accuracy	**0.72**	

4. CONCLUSIONS

The relationship between compressive strength with mixing and slenderness ratio of cylindrical concrete specimens was studied using ANOVA statistical methods. Furthermore, the discrimination model for mixing cylindrical concrete specimens has been studied by using machine learning algorithms, including support vector machine (SVM), linear discriminant analysis (LDA), k-nearest neighbor (k-NN), and random forest (RF). The mixing of aggregate and slenderness ratios is known to produce significant differences in the compressive strength of cylindrical concrete specimens ($p<0.05$). In particular, type-A and type-B of the type of concrete mixing significantly affect the compressive strength of cylindrical concrete specimens from further statistical tests using Duncan testing. Besides, the slenderness ratio has also significantly affected the compressive strength of cylindrical concrete specimens. LDA algorithm from machine learning can direct the discrimination of a mixture of cylindrical concrete specimens obtained by the core-drilling method from a slab block. It can be concluded that the outcomes of the machine learning model are encouraging and complement each other's statistically based experimental process control tools. This study figures that the LDA model's machine learning algorithm is more accurate in discriminating than the other machine learning models. Machine learning techniques are more appropriate and trustworthy when it is difficult to obtain experimental results or when the decision of an expert is essential.

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