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# DEVELOPMENT OF AI PREDICTIVE MODEL FOR MATHEMATICS LEARNING ACHIEVEMENT USING DEEP LEARNING

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**ABSTRACT**

In this study, a model for predicting learners' mathematics achievement was developed using deep learning technology. It was using a data set of mathematics characteristics and achievement data of first-year elementary school learners in Korea. Using this data, in this study, we developed an artificial intelligence model that predicts previous or subsequent performance based on the current mathematical performance. In this study, it is vital to consider the mathematical characteristics of learners to predict learning achievement. For this, cluster analysis was conducted on initial mathematical functions (number size, number order, number counting), computational fluency, and cognitive processing (work memory, processing speed). Next, based on the results of mathematics learning achievement, we developed an artificial intelligence model that can predict mathematics achievement before or after. The artificial intelligence model was developed using a sequence-to-sequence (seq2seq) model of a recursive neural network (RNN) method to use continuous data as input/output. The model predicting the achievement of Unit 3 <Addition and Subtraction> with the achievement of Unit 1 <Numbers up to 9> in the 1st grade showed more than 90% accuracy and more than 98% recall rate.

**Keywords:** *AI Model, Learning Achievement Prediction, Artificial Intelligence, RNN, Seq2Seq, Edutech*

## 1. INTRODUCTION

Recently, artificial intelligence has become a central technology for social change. Moreover, in the field of education, there is a growing interest in artificial intelligence. Artificial intelligence in education can be divided into education about artificial intelligence and a field that uses artificial intelligence technology educationally. The field of educational use of artificial intelligence technology is especially used in the field of edutech. The main purpose of utilizing artificial intelligence education in the edutech field is individualized, customized education [1]. This is because the AI model can use data to predict student characteristics and future achievements. This is because AI can achieve customized education suitable for students by recommending appropriate content for students. For the effectiveness of this education, Bloom presented the two-sigma problem in his research[2]. He researched students' learning achievements who received the general one-to-many form of lecture-style education and students who received one-to-one tutoring learning. As a result, it was found that the student's achievement, which is the top 2% of students who received one-to-many education, was the same as the average of the students who received one-to-one tutoring. This suggests the necessity of one-on-one tutoring education to improve students' academic achievement. In this context, various tutoring systems have been developed for customized education for each level of students[3]. Furthermore, currently, a tutoring system combining artificial intelligence technology is being applied in various subjects[4]. The purpose of this study is to support individualized and customized education for students. To this end, an artificial intelligence model suitable for Korean mathematics textbooks was developed. Specifically, In this study used students' mathematical characteristic data and learner's achievement data. Based on this data, an artificial

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intelligence model was developed to predict learners' future and previous achievements.

The model developed in this study can identify missing parts in the future or the past, depending on individual learners' mathematical characteristics. Based on this, the Model made in this study can prevent learners' learning deficits.Related research

## 2. RELATED RESEARCH

### 2.1 RNN(RECURSIVE NEURAL NETWORK)

In the realm of artificial intelligence research, various methodologies are explored to address complex problems. One such promising technique, as employed in this study, is the Recurrent Neural Network (RNN) approach. Distinctly characterized by its intrinsic recursive structure[5], an RNN stands apart from conventional neural networks. This unique feature empowers RNNs to recall previous data inputs, allowing them to adaptively modify subsequent results based on stored memories. Figure 1 offers a visual representation of the RNN's architecture. The exterior perspective of the RNN is depicted on the figure's left, while a more intricate view of its inner workings can be seen on the right. This dual presentation underscores the intricate balance between the RNN's simplicity in design and complexity in functionality.

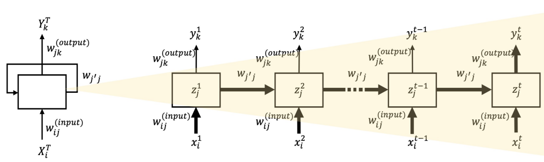

*Figure 1: Structure of a recursive neural network*

The Recurrent Neural Network exhibits a particularly intriguing characteristic: an internal recursive structure. This unique configuration is specifically tailored to efficiently learn from and remember prior states or sequences. In systems that operate on a reflexive basis, the hallmark of successful and effective learning is evident when it consistently and accurately predicts subsequent data points after receiving a step of continuous data. This predictive accuracy has significant ramifications for a multitude of applications. Due to this inherent capability, recursive neural networks have found their primary use in scenarios that demand analysis of continuous or sequential data streams[6]. The network's adeptness at handling such data makes it an invaluable tool for researchers and professionals in the field of data analysis and artificial intelligence.

### 2.2 SEQ2SEQ MODEL

The input data used in this study and the data output through the artificial intelligence model are continuous[7]. To create an RNN-type artificial intelligence model that can output such data types, it is necessary to develop a sequence-to-sequence artificial intelligence model. The sequence-to-sequence model is an artificial intelligence model that outputs the input of continuous data as continuous data. Moreover, this model can convert one sequence into another. The sequence-to-sequence model uses a recursive encoding network that embeds an input sequence in a vector space and a decoding network that enables sampling the output sequence[8].

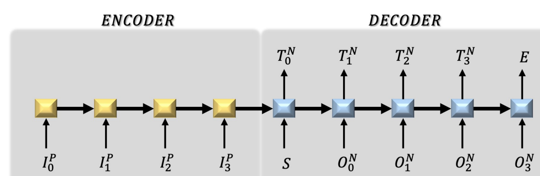


*Figure 2: Structure of a sequence-to-sequence model*

The sequence-to-sequence model is divided into an encoder and a decoder, as shown in Figure 2. The input value of the encoder is Inputbatch, and the final output value for the input value becomes the initial state of the decoder. Also, the decoder receives the final value of the encoder and performs iterative learning to accurately predict the Outputbatch as the TargetBatch value[9].

The form of data used for artificial intelligence learning can be inferred from the use of artificial intelligence. The artificial intelligence model to be developed in this study is a model that predicts previous or subsequent achievements based on the learner's current achievements. Therefore, the encoder part's input data used when learning artificial intelligence represents the learner's current mathematical achievement. Moreover, the input data of the decoder part corresponds to the achievements before or after. The process of predicting a result value using a sequence-to-sequence model is as follows. In prediction, there is input data but no output data. Therefore, the TargetBatch derived by setting the value of

Outputbatch to <Pad> is used as the predicted value. As shown in Figure 3. below, in the model, the continuous data, that is, the output value is determined according to the form of the previous input value. The output value dynamically changes according to each input value.

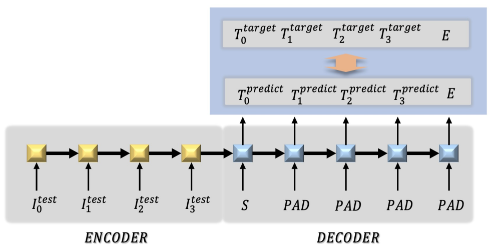


*Figure 3: Predict process of sequence-to-sequence model*

## 3. AI MODEL DESIGN METHOD

### 3.1. OVERVIEW OF AI MODEL DEVELOPMENT

Mathematical feature clustering is performed to predict each student's achievement in mathematics learning using an artificial intelligence model. *Clustering* is a technique used to analyze data and find clusters formed therein[10]. The characteristic mathematical data used for clustering are the initial mathematical function (number size, number order, number counting), computational fluency, and cognitive processing (working memory, processing speed) of the initial math test. Moreover, mathematics learning achievement used core achievements. Next, the achievement result data is classified according to the mathematical characteristics of the clustered learners. For example, when three optimal clusters are generated using the learner's mathematical characteristic data, the student achievement result data is also classified into three data based on the student's mathematical characteristics.

Based on this data, we develop an artificial intelligence model that can predict past or future achievements based on current achievements. Mathematics has a distinctive curriculum characteristic. Therefore, previous learning achievements have a close influence on subsequent learning achievements. Accordingly, it is necessary to consider this part when designing an artificial intelligence model that predicts a mathematics subject's achievement. Therefore, it is necessary to use the RNN technique, an artificial intelligence model that can memorize previous data. The output value according to the continuous data input value representing the current core achievement has continuous data. In consideration of these characteristics, the sequence-to-sequence (seq2seq) technique was used among the RNN techniques. To evaluate the model as to whether artificial intelligence can effectively predict, the model's prediction accuracy (Accuracy) and recall (AUC) were measured[11].

### 3.2. Clustering Of Mathematical Features By Student

Clustering was performed based on the initial mathematical function (number size, number order, number counting), computational fluency, and cognitive processing (work memory, processing speed), which are datasets that can infer the learner's mathematical characteristics. In this study, K-means++ was used as the clustering technique. There is the Elbow technique and the Silhouette technique to find the optimal cluster[12]. In this study, the silhouette technique was used. The silhouette technique is a method of evaluating clusters considering the distance and density of the clusters[13]. This method assumes that good clusters are separated from each other and that the clusters' internal density is high. So, it is an optimized method for evaluating K-mean clustering. For clustering, initial mathematical function (number size, number sequence, number counting), computational fluency, and cognitive processing (work memory, processing speed) data were flattened and then clustered using the K-means++ technique. Moreover, to find Moreover an optimal number of clusters, 2 to 10 clusters were performed. Moreover, the result of applying the silhouette technique according to the number of each cluster is shown in Figure 4.

Clusters are classified by color, from 0 to the right, the closer to 1, and the left, the closer to -1. Data having a negative silhouette index may be judged to have a high probability that the number of clusters for the data is not appropriate[14]. Also, the thickness of the cluster represents the score of each data silhouette. The top point represents the highest score in the graph, and the bottom point represents the lowest score. As the thickness is constant, it can be said that the clustering is suitable. As a result of clustering, the silhouette scores' average was the highest when there were two clusters. Moreover, it can be seen that the thickness of the clusters is also uniform compared to the number of other clusters. Accordingly, it can be determined that the number of clusters optimized for this study data is two. Based on this result, the student's mathematics achievement data set was clustered into a data set by learner's characteristics. To this end, the data clustered into two, which is the number of clusters optimized for this dataset, and the result data of learners' mathematics were merged.

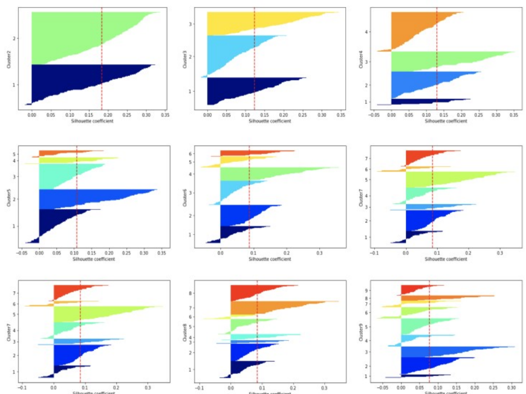

*Figure 4: Result of applying the silhouette technique according to each cluster number*

### 3.3. Data Used For Artificial Intelligence Model Development

The data used to develop the artificial intelligence model are measured data for 301 students in the first grade of elementary school. Specifically, it is the initial mathematical function (number size, number sequence, number counting), computational fluency, cognitive processing (work memory, processing speed), which are components of the predictive measurement tool, and the core achievement result from data of the unit.

### 3.4. Predictive Ai Model Development

The artificial intelligence model developed in this study uses learners' mathematical characteristics and achievement result data for each unit. Moreover, through this, it predicts the core achievements of the unit before or after. A sequence-to-sequence artificial intelligence model is developed using the clustered mathematics achievement data based on the learner's mathematical characteristic data.

The artificial intelligence model's input data for predicting mathematics subject achievement is the result data of core achievements for each unit of students. Figure 5 shows the execution process of the developed artificial intelligence model. The artificial intelligence model's input data for the prediction of mathematics subject achievement is the result data of core achievements for each unit of students. The achievement result data for each unit is organized in the form of a one-dimensional array. Array elements have values of 1 and 0. Each core achievement has a value of 1; otherwise, it has a value of 0. The output data of the artificial intelligence model, like the input data, represents the nuclear achievement results of the previous or subsequent units. Moreover, the shape is a one-dimensional array. The data in this array also has a value of 1 when the core achievement is reached. Furthermore, if it has not reached, it has a value of 0. As shown in Figure 5, if the achievement result corresponding to unit 3 is input into artificial intelligence, the achievement result corresponding to unit 5 of the student can be predicted.

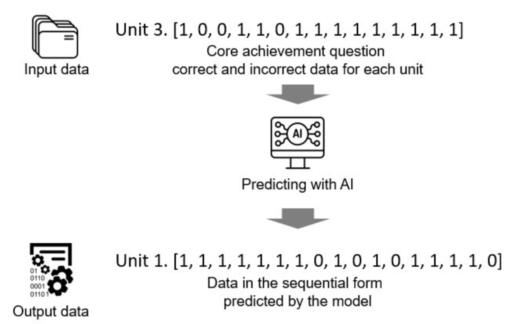


*Figure 5: Process of model prediction*

The number-related units in the first-year mathematics subject of an elementary school in Korea are Units 1, 3, and 5. In contrast, since Units 2 and 4 were related to figures, this study developed models based on Units 1, 3, and 5. This study developed a model that predicts future learning achievement and a model that predicts previous learning achievement. To predict future learning achievement, a model was developed that predicts Unit 3 from Unit 1. Moreover, for predicting previous learning achievement, a model was developed that predicts Unit 3 from Unit 5.

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## 4. PREDICTIVE MODEL PERFORMANCE EVALUATION

For the performance evaluation of the artificial intelligence model, an artificial intelligence model was used to predict the core achievements of the unit 3 <addition and subtraction> using the core achievements of the unit 1 <Numbers up to 9>. As a result of clustering by learner characteristics, two clusters were presented as the most optimized clusters. Therefore, the learner's core achievement data was divided into two clusters. Accordingly, each model was developed to predict achievement for each of the two clusters. To measure the model's accuracy and recall, 80% of the total data was used as training data, and 20% of the data was used as experimental data. Besides, the epoch for learning was set to 1,000, and the batch size was set to 100.

### 4.1. EVALUATING THE PERFORMANCE OF AN ARTIFICIAL INTELLIGENCE MODEL THAT PREDICTS THE ACHIEVEMENT OF UNIT 3 WITH UNIT 1

The first model is a model that predicts the achievement of Unit 3 <Addition and Subtraction> based on the achievements of Unit 1 <Numbers up to 9> in the 1st semester of Mathematical Characteristic Group 1 students. The accuracy of the model is the accuracy of the test data. It can be seen that the accuracy of the test data continues to increase as learning progresses. However, as shown in Figure 6., when the Loss value is increasing from 500 epochs, it is judged that overfitting occurs from 500 epochs.

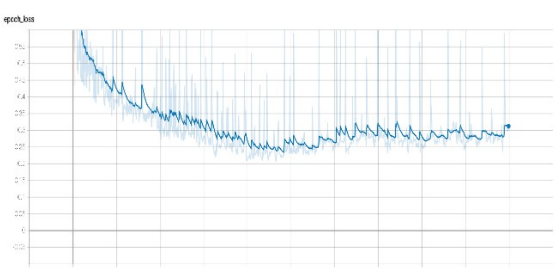

*Figure 6: The loss value of the model that predicts the learning achievement of Unit 3 with Unit 1 in the first group*

After 1,000 epochs, the accuracy was 92%, and the recall was 99%. The accuracy of each epoch is as shown in Figure 7., and the recall is as shown in Figure 8.

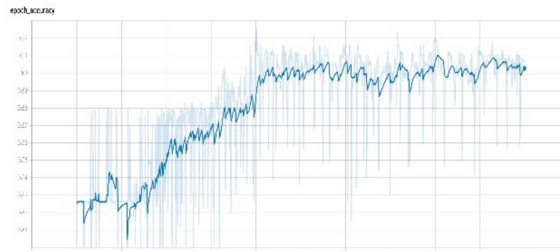

*Figure 7: The accuracy of the model that predicts the learning achievement of Unit 3 with Unit 1 in the first group*

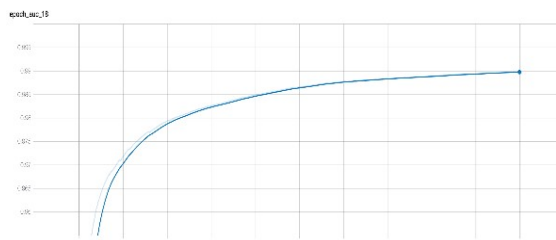

*Figure 8: The recall rate of the model that predicts the learning achievement of Unit 3 with Unit 1 in the first group*

The second model is a model that predicts the achievement of the addition and subtraction of Unit 3 based on the achievement of the numbers (1-A-1) up to Unit 9 in the 1st semester of the Mathematical Characteristic Group 2 students. The accuracy of the model is the accuracy of the test data. It can be seen that the accuracy of the test data continues to increase as learning progresses. However, as shown in Figure 9., when the Loss value is increasing from 500 epochs, it is judged that overfitting occurs from 500 epochs.

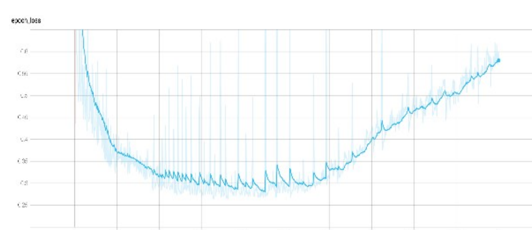

*Figure 9: The loss value of the model predicting the learning achievement of Unit 3 from Unit 1 in the second group*

As can be seen from the Loss value, it can be seen that after 500 epochs, overfitting of the training data appears and the accuracy of the experimental data decreases. At 500 epochs of this

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model, the accuracy was 90%, and the recall was 98%. The accuracy of each epoch is as shown in Figure 10., and the recall is as shown in Figure 11.

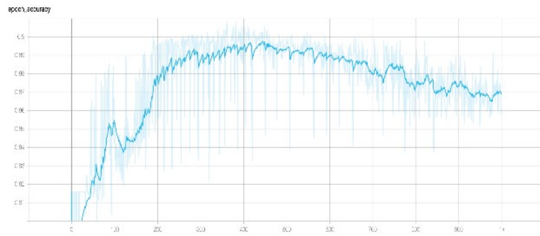

*Figure 10: The accuracy of the model predicting the learning achievement of Unit 3 from Unit 1 in the second group*

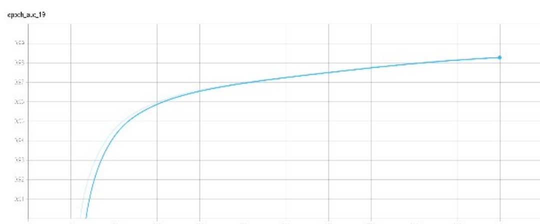

*Figure 11: The recall rate of the model predicting the learning achievement of Unit 3 from Unit 1 in the second group*

One of the reasons that the accuracy of the model developed in this study is 90% is judged to be due to the training data's characteristics. In order to develop an artificial intelligence model that shows high accuracy using training data composed of input data and output data, the output data for the same input data must be identical. However, for the data used in the study, the high prediction was not made because the values of the output data for the same input data were different. To solve this problem, it is necessary to learn the data of input data and output data by configuring clusters according to learner's mathematical characteristics in various ways.

### 4.2. Evaluating The Performance Of An Artificial Intelligence Model That Predicts The Achievement Of Unit 3 With Unit 5

The first model is a model that predicts the core achievements of Unit 5 <Numbers up to 50> based on the core achievements of Unit 3 <Addition and Subtraction> of students in the Mathematical Characteristic Group 1 group. The accuracy of the model is the accuracy of the test data. As shown in Figure 12., when the Loss value is increasing from 650 epoch, it is judged that overfitting occurs from 650 epoch.

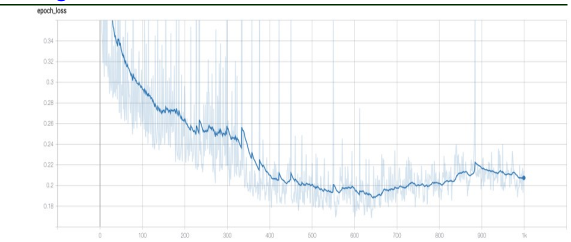

*Figure 12: The loss value of the model that predicts the learning achievement of Unit 3 with Unit 5 in the first group*

After 600 epochs, the accuracy was 94%, and the recall was 99%. The accuracy of each epoch is as shown in Figure 13., and the recall is as shown in Figure 14.

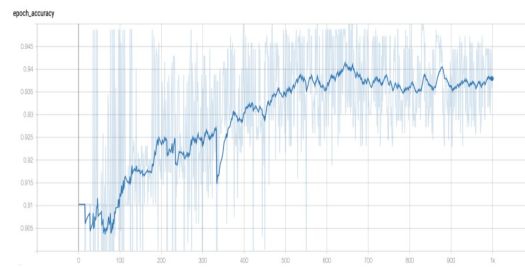

*Figure 13: The accuracy of the model that predicts the learning achievement of Unit 3 with Unit 5 in the first group*

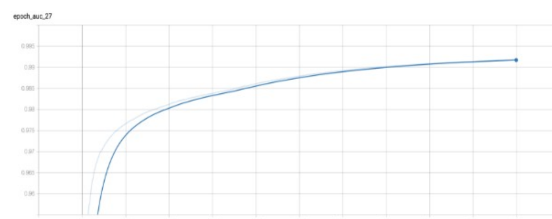

*Figure 14: The recall rate of the model that predicts the learning achievement of Unit 3 with Unit 5 in the first group*

The second model is a model that predicts the core achievements of Unit 1-A-5 based on the core achievements of Unit 1-A-3 of the students in the Mathematical Trait 2 cluster. The accuracy of the model is the accuracy of the test data. It can be seen that the accuracy of the test data continues to increase as learning progresses. However, as shown in Figure 15., when the Loss value is increasing from 300 epochs, it is judged that overfitting occurs from 300 epochs.

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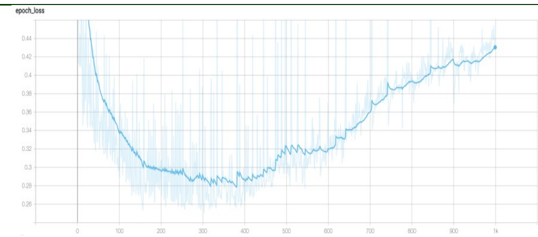

*Figure 15: The loss value of the model predicting the learning achievement of Unit 3 from Unit 5 in the second group*

As can be seen from the Loss value, it can be seen that after 300 epochs, overfitting of the training data appears and the accuracy of the experimental data decreases. At 300 epochs of this model, the accuracy was 91.5%, and the recall rate was 97.5%. The accuracy of each epoch is as shown in Figure 16., and the recall rate is as shown in Figure 17.

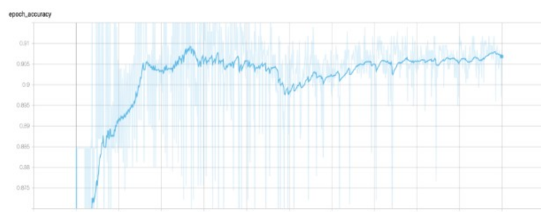

*Figure 16: The accuracy of the model predicting the learning achievement of Unit 3 from Unit 5 in the second group*

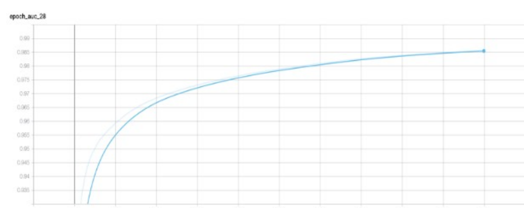

*Figure 17: The recall rate of the model predicting the learning achievement of Unit 3 from Unit 5 in the second group*

To develop an artificial intelligence model that exhibits high accuracy using training data composed of input data and output data, the output data for the same input data must be the same. However, some of the data used in the study were not trained accurately because the values of the output data for the same input data were different. Even in the same artificial intelligence learning situation, the accuracy of the model predicting Unit 3 <addition and subtraction> with Unit 1 <Number up to 9> and the model predicting Unit 5 <Number up to 50> with Unit 3 <Addition and Subtraction> There was a difference. It is assumed that the cause of this difference is the overlapping of achievement data clustered by mathematical characteristics.

Therefore, in Unit 3 <Addition and Subtraction>, which has a high correlation between the cluster by the learner's mathematical characteristics and the achievement of the unit, Unit 5 <Numbers up to 50> has a relatively low correlation, and Unit 1 <Numbers up to 9>. As a result, it showed higher accuracy than Unit 3 <Addition and Subtraction>. This can be seen as a difference in the accuracy of the model because the homogeneity of the core achievement data for each cluster is high. Therefore, to develop an artificial intelligence model with high accuracy, it is necessary to execute clusters for each mathematical characteristic and construct input data and output data in consideration of predictive factors and sophisticated data analysis results that are highly correlated with mathematical learning achievements.

## 5. CONCLUSION

In this study, we developed an artificial intelligence model that predicts individual students' core achievements before or after units in consideration of learners' mathematical characteristics. To this end, first, the learner's mathematical characteristic data was analyzed. Cluster analysis was conducted on initial mathematical functions (number size, number sequence, number counting), computational fluency, and cognitive processing (working memory, processing speed). As a result, the number of optimized clusters was 2 in the silhouette analysis for cluster optimization. The data clustered by mathematical characteristics and the learner's core achievement data were merged, and as a result, the learner's core achievement data were divided into two.

Next, based on the results of mathematics learning achievement, we developed an artificial intelligence model that can predict mathematics achievement before or after. The AI model was developed using a sequence-to-sequence (seq2seq) model of a recursive neural network (RNN) method to use continuous data as input/output.

The accuracy and recall were verified by developing an artificial intelligence model for each cluster that can predict Unit 3 with the achievement of Unit 1, as well as a model predicting Unit 5 with Unit 3, respectively.

The model predicting the achievement of Unit 3 <Addition and Subtraction> with the achievement

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of the first Unit 1 <Numbers up to 9> showed an accuracy of more than 90% and a recall rate of more than 98%. The model that predicted the achievement of Unit 5 <Numbers up to 50> with the second Unit 3 <Addition and Subtraction> showed that the accuracy was 94% and the recall rate was 99%. To increase the accuracy of the model created in the future, it is necessary to elaborate the learner's characteristic cluster through data acquisition and secure diversity of key achievement data.

In this study, we implemented a method of developing an artificial intelligence model for predicting experimental mathematics achievement by learner's characteristics by using student's mathematical characteristic data. Through this, the possibility of developing artificial intelligence models and technical application in mathematics subjects was suggested. Also, it has the following implications.

First, the mathematics learning prediction model can predict not only future achievements but also achievements in previous units based on student achievements in the current unit. Therefore, it is possible to predict whether the current student's underachievement is mainly affected by the deficit in which unit, and what positive changes will occur in subsequent learning successively when the student successfully performs supplementary education for the unit.

Third, in the artificial intelligence prediction model, the current achievement and future student achievement can be specifically scored and provided with high accuracy. Along with this, if unit evaluation and data analysis of a measurement tool for predicting basic mathematics is used, the characteristics of learners related to mathematics learning and currently in a particular group (e.g., above average, low achievement, risk group, etc.). It can also provide information to instructors about which group they are likely to be in for future learning. Above all, the tool for predicting basic mathematics can also obtain information on the student's characteristics. Therefore, it can be provided as helpful information in teaching and learning about what level of supplementary education is needed (e.g., predicting initial response, level of supplementary education, etc.) according to the degree of learning deficit. Besides, it suggests the possibility of further developing a recommendation model suitable for students based on this data.

The suggestions of this study are as follows. The RNN-based model has a disadvantage in that it has a large amount of computation and does not reflect the characteristics of each instance of learning of the encoder part well. The attention method is a technique that can solve this problem [15]. Therefore, it is necessary to develop a model that can complement the existing research using an attention-based model.

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