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Research Article

Prediction of Metacognition Awareness of Middle School Students: Comparison of ANN and ANFIS with Statistical Techniques

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Abstract

Problem-solving skill is one of the most important skills that an individual should have today. Reflection can best be observed in the problem-solving process because reflective thinking occurs when a particular problem is perceived. Since reflective thinking features are related to the individual's own thinking processes, it has the feature of being a predictive variable for metacognition. This study's main goal is to create models that predict middle school students' mathematical metacognition awareness through reflective thinking characteristics towards mathematical problem solving utilizing Artificial Neural Network (ANN) and the Adaptive Neuro-Fuzzy Inference System (ANFIS). Mathematics academic achievement scores, cumulative grade point average (GPA), and reflective thinking characteristics of students towards mathematical problem solving were used as input parameters while constructing the ANN and ANFIS model, and mathematical metacognition awareness of students served as the only output parameter. In addition, the system was trained using 70% of the data to build the ANFIS model. Feed-forward backpropagation with the Levenberg-Marquardt learning algorithm was used to train the network for ANN model. Statistically, there is no significant difference between the students' actual metacognitive awareness scores and the artificial ANFIS and ANN metacognitive awareness scores. These findings showed that the created models performed successfully in predicting the mathematical metacognitive awareness of middle school students through their academic achievement (general and mathematics) and reflective thinking features for problem-solving. This study serves as an excellent example of how artificial intelligence can be used to anticipate certain educational traits of students. Different applications of artificial intelligence in the area of education can be obtained by varying the methodologies employed in the research.

Keywords: ANN, ANFIS, Artificial Intelligence, Mathematical Metacognition Awareness, Reflective Thinking Skill, Problem Solving.

Ortaokul Öğrencilerinin Üstbiliş Farkındalıklarının Yordanması: YSA ve ANFIS'in İstatistiksel Yöntemlerle Karşılaştırılması

Öz

Problem çözme becerisi, günümüzde bireyin sahip olması gereken en önemli becerilerden birisidir. Yansıtma en iyi problem çözme sürecinde gözlemlenebilir çünkü yansıtıcı düşünme belirli bir problem algılandığında ortaya çıkar. Yansıtıcı düşünme özellikleri bireyin kendi düşünme süreçleri ile ilgili olduğundan üst biliş için yordayıcı bir değişken olma özelliğine sahiptir. Bu çalışmanın temel amacı, Yapay Sinir Ağı (YSA), Uyarlanabilir Nöro-Bulanık Çıkarım Sistemi (ANFIS) kullanarak matematiksel problem çözmeye yönelik yansıtıcı düşünme özellikleri aracılığıyla ortaokul öğrencilerinin matematiksel üstbiliş farkındalıklarını tahmin eden modeller oluşturmaktır. YSA ve ANFIS modelleri oluşturulurken öğrencilerin matematik dersi başarı puanları, kümülatif genel not ortalamaları ve matematiksel problem çözmeye yönelik yansıtıcı düşünme özellikleri girdi parametreleri olarak ve matematiksel üstbiliş farkındalıkları çıktı parametresi olarak kullanılmıştır. Ayrıca sistemde, ANFIS modelini oluşturmak için verilerin %70'i kullanılarak eğitilmiştir. Yapay sinir ağını eğitmek için Levenberg-Marquardt öğrenme algoritması ile ileri beslemeli geri yayılım kullanılmıştır. İstatistiksel olarak, öğrencilerin gerçek üstbiliş farkındalık puanları ile yapay olarak elde edilen ANFIS ve ANN üstbiliş farkındalık

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puanları arasında anlamlı bir fark yoktur. Bu bulgular, oluşturulan modellerin ortaokul öğrencilerinin akademik başarıları (genel ve matematik) ve problem çözmeye yönelik yansıtıcı düşünme özellikleri aracılığıyla matematiksel üstbilişsel farkındalıklarını yordamada başarılı performans gösterdiğini kanıtlamaktadır. Ayrıca çalışma, öğrencilerin eğitimsel bazı özelliklerini tahmin etmek için yapay zekanın nasıl kullanılabileceğinin bir örneğidir. Araştırmada kullanılan metodolojiler çeşitlendirilerek eğitim alanında farklı yapay zeka uygulamaları gerçekleştirilebilir.

Anahtar Kelimeler: YSA, ANFIS, Yapay Zeka, Matematiksel Üstbiliş Farkındalığı, Yansıtıcı Düşünme Becerisi, Problem Çözme.

1. Introduction

When the literature on reflective thinking is examined, it is seen that there is great confusion in the definitions made. It can be said that this situation is due to its use in different fields and the breadth of the word meaning. It is seen that the concept of reflection is used synonymously with the concepts of problem-solving, reflective judgment, reasoning, questioning, reviewing, reflective thinking, critical reflection, and reflective practice (Moon, 1999). The concept of "reflective learning" was first used by Vilhelm von Humboldt about 200 years ago. Humboldt revealed the expansion of learning how to learn as well as learning (Fichtner, 2005). In addition, reflection was introduced by John Dewey in 1933 with the approach of learning by doing. Dewey (1933) defines reflective thinking as an active and deliberate process in which knowledge and beliefs are taken into account and related ideas are sequenced by reasoning. Reflective thinking has different aspects from the processes we apply in the name of thinking in that it includes activities such as hesitation, doubting the situation, mental difficulty, being surprised and searching, questioning, hunting, and finding material to remove doubt (Dewey, 1933). Schön (1987) considered projection in two ways: reflection during action and reflection upon action. Reflection on action is evaluating every aspect of the action after the action has taken place, looking back, and thinking about the action in a systematic and deliberate way. In-action reflection is the process that focuses on solving the problems that arise while performing the action instantly and includes the reorganization of the action (Schön, 1987). According to Heppner, problem-solving and coping with problems are synonymous. The concept of problem-solving in real life has been considered as the act of directing cognitive and emotional processes to a goal with the aim of adapting to internal or external requests or calls (Katkat and Mızrak, 2003). In Schonfeld's theory of problem-solving, there are some stages in solving mathematical problems: analysis of the problem, selection of appropriate mathematical information, planning, implementing of the plan, and checking the answer (Harskamp and Suhre, 2007). Problem-solving skill is one of the most important skills that an individual should have today. In this sense, it is predicted that reflective thinking will contribute to the problem-solving process. Reflection can best be observed in the problem-solving process because reflective thinking occurs when a particular problem is perceived (Shermis, 1992).

Since reflective thinking features are related to the individual's own thinking processes, it has the feature of being a predictive variable for metacognition. In the early 1970s, John Flavell introduced the concept of metacognition, basing this concept on the term meta-memory he had conceived before (Aydın and Ubuz, 2010). The assumption that the concept of metacognition consists of monitoring and regulation components was first put forward by Flavell (1976). In the following years, Flavell further developed his studies and defined the concept of metacognition as knowledge about objects or events perceived cognitively (Flavell, 1979). In later years, Flavell further developed the definition of metacognition and defined it as the individual's knowledge of his own cognitive processes and using this knowledge to control his cognitive processes (Flavell, 1987). When the literature is examined, it is seen that the concept of metacognition is considered as a framework and this framework is defined as a structure consisting of certain components. Metacognitive knowledge, metacognitive control, and metacognitive experience are the three components of this framework (Özsoy, 2008). Metacognitive knowledge can be explained as knowledge of cognition, metacognitive control can be explained as regulation of cognition and metacognitive experience can be explained as a sense of knowing or perception of learning (Özsoy, 2008; Karakelle and Şentürk, 2006). The strategy knowledge required to successfully complete cognitive strategies can be explained as metacognitive knowledge (Karakelle and Saraç, 2007). Metacognitive knowledge is divided into three: procedural (procedural) knowledge, descriptive (declarative) knowledge, and state (conditional) knowledge (Schraw and Moshman, 1995). Knowledge of how to successfully complete a cognitive task is procedural knowledge (Özsoy and Günindi, 2011). An example of procedural knowledge is the sentence "I know how to solve a radical number problem". An individual's knowledge of his own abilities, metacognitive goals, and factors that will affect his performance is explanatory information (Montgomery, 1992). An example of explanatory information is the sentence "I know whether I can solve a radical number problem". Information about when, why, and why to use descriptive and procedural knowledge is situational knowledge (Woolfolk, 2004). An example of situational information is the sentence "I can choose the strategy I will use when solving a radical number problem and I know why I use that strategy". The metacognitive control component is divided into three: planning, monitoring, and evaluation. Planning consists of selecting appropriate strategies, and resources before starting a task (Yıldız et al., 2009). Before starting to work, features such as paying attention, setting goals, estimating, and scheduling are included in planning (Schraw and Moshman, 1995). The sentence "I prepare for the subject to be covered before the mathematics lesson" can be given as an example of planning. Monitoring is about being aware of one's own performance while performing a cognitive task (Özsoy and Günindi, 2011). In addition, features such as identifying performance errors and making predictions about future performance are included in monitoring (Schraw, 2009). The sentence "I think about how I can use what I have learned about square root numbers in other subjects" can be given as an example for monitoring. Evaluation is concerned with the individual's evaluation of the efficiency of the learning process and learning outcomes (Everson and Tobias, 1998). The sentence "After studying the subject of permutation, I will give myself a test on that subject" can be given as an example for the evaluation. The metacognitive awareness of the students, in general, may not adequately reflect their metacognitive awareness for a specific lesson. Since mathematics is separate from other disciplines by its nature, metacognition can be evaluated separately for the mathematics course.

With the use of conventional mathematical techniques, it is doubtful that a model based on randomly chosen and unpredictable processes can be successful. However, even without precise quantitative data, a fuzzy inference approach that applies fuzzy if-then rules has a decent chance of simulating the qualitative aspects of human understanding and reasoning (Sugeno, 1985; Garcia et al., 1997). The fuzzy logic technique designed by Zadeh is one of the most successful artificial intelligence methods (Zadeh, 1996).

Artificial Neural Networks (ANN) provide a number of advantages, including as imitating the human brain and doing tasks while learning. Additionally, ANN may organize itself while performing tasks, which is not achievable for conventional computer systems. Moreover, ANN can run in parallel, whereas regular computer programs cannot. Furthermore, ANN is quite quick, whereas human brain processing is considerably slower than ANN (Kukreja, 2016). Whereas ANN has a great number of benefits, it also has certain drawbacks. For instance, the ANN has no fixed method of operation. The final product's quality can frequently be unexpected and inappropriate. Additionally, the majority of ANN algorithms do not offer a repair or guidance for issues found in the final output (Sharma et al., 2012). Overfitting is another significant problem with ANNs: in the output, they produce greater error values than they did in their training sets (Dongare, 2012). Considering these drawbacks, ANN is still widely utilized in the present to resolve a wide range of scientific issues for its beneficial equivalents.

The primary benefit of the neuro-fuzzy system is that it combines the advantages of neural networks with fuzzy logic, therefore removing the drawbacks of both. While neural networks deal with implicit knowledge acquired through learning, fuzzy logic deals with the knowledge that may be acquired and comprehended explicitly (Singh et al., 2012). ANFIS integrates the qualitative approach of fuzzy logic and the adaptability of neural networks into one system (Jagtap and Pillai, 2014). Along with its benefits, it also has certain drawbacks. In a fuzzy system, membership criteria and rules are developed through a process of trial and error. To understand the proper membership function and rules for a sophisticated system and arrive at a well-founded solution, a significant amount of time is needed. Additionally, the fuzzy system's generalization potentiality is relatively low (Singh et al., 2012). Therefore, in this study, the metacognition awareness of middle school students has been predicted using both the ANFIS and ANN approaches. The trial data have also been used to validate the proposed models. As long as the models function satisfactorily, they can serve as guiding principles for the creation of additional models for artificial intelligence-based prediction systems for education.

2. Materials and Method

In this study, mathematical metacognitive awareness of middle school students was evaluated and compared with the designed fuzzy logic and artificial intelligence-based models. The inputs of the study were determined as the students' mathematics achievement scores and cumulative grade point average (GPA), their reflective thinking towards mathematical problem solving, and the output was their mathematical metacognition awareness. To predict students' mathematical metacognitive awareness, artificial neural networks (ANN), and adaptive neuro-fuzzy inference system (ANFIS) models were established and comparisons were made.

For this purpose, this research is in the general survey model and is descriptive in nature. In the general survey model, in a universe consisting of many elements, research is conducted on the entire universe or a group of samples or samples to be taken from it in order to reach a general judgment about the universe (Büyüköztürk, 2012). In survey research, researchers are more concerned with how ideas and characteristics are distributed among the individuals in the sample rather than why they arise (Fraenkel and Wallen, 2006).

2.1. Participants

The participants of the research are 266 middle school students studying at different grade levels in the European side of Istanbul. Of the participants, 87 (33%) were fifth graders, 30 (11%) were sixth graders, 60 (23%) were seventh graders, and 89 (33%) were eighth graders. In this study, the convenience sampling method was used. The convenience sampling approach is used to include individuals who meet certain functional requirements, such as easy accessibility, geographic proximity, and voluntary participation in studies (Johnson and Christensen, 2014).

2.2. Data Collection Tools

Three data collection tools were used for the research. The characteristics of each of the data collection tools are given below.

2.2.1. Information Form

In this form, there are parts related to the personal information of the students. Grade level, gender, mathematics course score, GPA information is included. GPA and mathematics achievement scores were used for this research. The reason is that these two variables are suitable for evaluation with fuzzy logic.

2.2.2. Mathematical Metacognition Awareness Scale

This measurement tool was developed by Kaplan and Duran (2016) to reveal the mathematical metacognition awareness of middle school students (Kaplan and Duran, 2016). Students' metacognitive awareness is multifactorial variables that cannot be observed directly. At the end of the analysis, the Cronbach Alpha reliability coefficient of the 23-item scale was calculated as .905. As a result of the explanatory factor analysis, it was determined that the items forming the scale were grouped under three factors and the total variance rate explained by these factors was 43.12%. Eight items collected in the first factor were named "mathematical knowledge", eight items collected in the second factor were named "mathematical monitoring", and the last factor consisting of seven items was named "mathematical determination". As a result of confirmatory factor analysis, it was determined that the three-factor model had sufficient fit indices. As a result, the scale is a valid and reliable measurement tool that can be used in middle school mathematics courses. In the present study, Cronbach's α was calculated as 0.82 for the whole scale, and 0.81, 0.83, 0.88 for each factor, respectively.

2.2.3. Reflective Thinking Skills Scale for Problem Solving

This measurement tool was developed by Kızılkaya and Aşkar (2009) to be used in determining the reflective thinking skills of students for problem-solving (Kızılkaya and Aşkar, 2010). By examining the actions that reveal reflective thinking, three dimensions of reflective thinking: questioning, reasoning and evaluation were determined. The scale includes 14 items. Kaiser-Meyer-Olkin (KMO) and Bartlett tests were performed to determine the suitability of the data for factor analysis. The KMO value was "0.872" and the Bartlett's Test of Sphericity value was 1084.329 ($p < 0.01$). As a result of the confirmatory factor analysis within the framework of the validity studies of the problem-solving reflective thinking skill scale, the fit indices were GFI= 0.92, AGFI= 0.89, NNFI= 0.93, CFI= 0.95, RMSR= 0.08, RMSEA = 0.071. calculated. Cronbach Alpha values were examined for the reliability proofs of the factors. According to the results of the analysis, the value of the questioning factor was 0.73, the value of the reasoning factor was 0.71, and the value of the evaluation factor was 0.69. This value was calculated as 0.83 for all scale items. In the present study, Cronbach's α was calculated as 0.79 for the whole scale, and 0.70, 0.71, 0.70 for each factor, respectively.

3.1. Development of ANN and ANFIS Prediction Model

3.1.1. The fundamental design of artificial neural network (ANN)

Highly parallel computer systems called artificial neural networks (ANNs) are modeled after biological neural networks (Majumder, 2015). In simulating the structure of the human biological brain, artificial neural networks (ANNs) were originally developed in the 1950s (Viotti et al., 2002). A signal pattern provided to the network as an input can be internally represented by an ANN. The strength of network connections connected with each neuron is dynamically changed to facilitate this automated processing or "learning" (Hepner, et al., 1990).

Input neuron layers (or nodes, units) make up an artificial neural network, together with one or more hidden neuron layers and an output neuron layer in the final layer. Figure 1 illustrates the general design of an ANN. Each connection has a weight that is a numeric value. Eq. (1) can be used to express the output, h_i, from neuron i's final layer in the hidden layer (Khan, 2018).

$$h_i = \sigma\left(\sum_{j=1}^{N} V_{ij}x_j + T_i^{hid}\right) \quad (1)$$

in which σ is the activation function, N is the number of input neurons, V_{ij} are the weights, x_j are the inputs of the input neurons, and T_i^{hid} are the threshold terms of the hidden neurons.

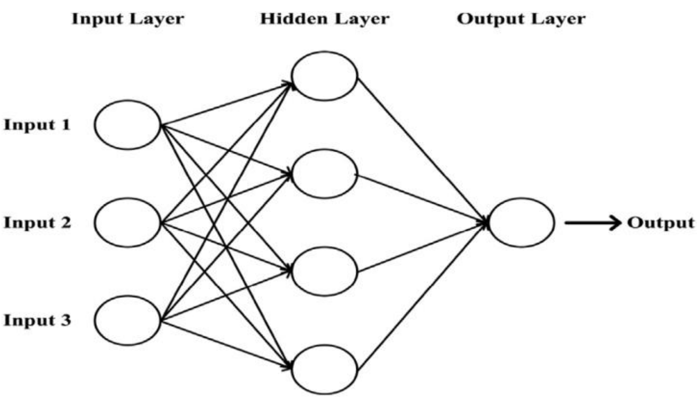


Figure 1. The general structure of a neural network (Sarkar, et al., 2021).

The output of a given input is predicted by ANN using a learning technique. The two main categories of ANN learning are supervised learning and unsupervised learning. Training is required in supervised learning to help the system predict the outcome. In order to reduce errors, weights are modified in the training to desirable values. Examples of previous data are presented during such training sessions, and the ANN system receives inputs and related outputs. In contrast, unsupervised training lacks any precedent examples in its database, and ANN attempts to predict the outcome using patterns and trends (Zou, 2008)

3.1.2. Development of ANN Model

We used the MATLAB NN toolbox for this study. The students' achievement grades and GPA, and their reflective thinking towards mathematical problem solving were the input variables for the feed-forward neural network. The output variable in the output layer was decided to be their mathematical metacognition awareness. The network was designed utilizing 3 neurons for the input layer, 10 neurons for the hidden layer, and 1 neuron for the output layer. This is known as a 3-10-1 structure. In contrast to the hidden layer and output layer, where log-sig and purelin transfer functions, respectively, have been utilized, the input layer did not use a transfer function. The network was trained using a feed-forward backpropagation method and the Levenberg-Marquardt learning algorithm. 266 datasets altogether were used to build the ANN prediction model. The system was trained using 70% of the datasets (186 datasets), while the other 30% were equally allocated for testing and validation (Hossain et al., 2017). To compare the results with the experimental and ANFIS model projected outcomes, all 30% were chosen in this study as the test set. The datasets used to test the model were also chosen at random in order to test the ANN prediction model.

3.1.3. The Fundamental Design of Adaptive Neuro-Fuzzy Inference System (ANFIS)

In our daily lives, we must deal with a variety of unpredictable situations. The fuzzy inference approach makes it possible to describe unclear situations as rules during the decision-making process. Therefore, many issues have been solved with it (Lochan and Roy, 2015; Karaboga and Kaya, 2019). Neuro-fuzzy systems often have the advantage of making things simpler than when using standard neural networks because they combine ANN and fuzzy networks (Walia, 2015).

The architecture of ANFIS consists of five layers: the fuzzy layer, the product layer, the normalized layer, the de-fuzzy layer, and the overall output layer. Figure 2 displays every one of those five layers. The fuzzy inference method can be thought of as having two inputs (v and d) and one output (f), for simplicity. Below is a brief description of each of the five ANFIS algorithm layers (Walia, 2015).

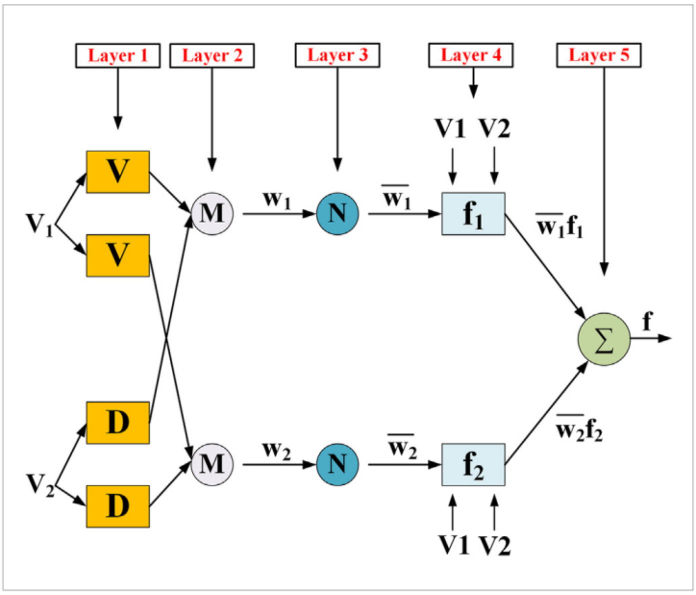


Figure 2. The architecture of ANFIS (Sarkar, et al., 2021).

Each node in layer one's fuzzy, adaptive layer is a fuzzy node. The system's inputs are v and d in this layer, while O1 is layer 1's ith node's output. As shown by Eqs. (2) and (3), all of the adaptive nodes are square nodes with square functions.

$$O_{1,i} = \mu_{v,i}(V) \; for \; i = 1{,}2. \quad (2)$$

$$O_{1,j} = \mu_{d,j}(V) \; for \; j = 1{,}2. \quad (3)$$

The output functions in this equation are represented by $O_{1,i}$ and $O_{1,j}$, whereas the membership functions are represented by $\mu_{v,i}$ and $\mu_{d,j}$. Selecting a triangle function

$$\mu_{v,i}(V) = max\left[\min\left(\frac{v-a_i}{b_i-a_i}, \frac{c_i-v}{c_i-b_i}\right), 0\right] \quad (4)$$

The parameters of triangular membership functions are $\{a_i, b_i, c_i\}$. Once more, if we want $\mu_{v,i}(V)$ to have a bell form.

$$\mu_{v,i}(V) = \frac{1}{1+\left\{\left(\frac{v-c_i}{a_i}\right)^2\right\}b_i} \quad (5)$$

Layer 2 investigates the weights of each membership function using the input value vi from Layer 1 as its starting point. The output is calculated using the product of all incoming signals at the fixed, M-labeled nodes of this layer. This layer's output can be expressed in Eq (6).

$$O_{2,i} = w_i = \mu_{v,i}(V).\mu_{d,j}(D), \quad i = 1{,}2. \quad (6)$$

4. Results

4.1. Data Prediction by ANN Model

The ANN model illustrated in Figure 3, whose network type is feed-forward backpropagation, is tested with 3 neurons.

Layer 3 nodes are identified by the letter N, which denotes normalization to the firing strength from layer 1. Precondition matching of fuzzy rules is done in this layer. This layer's output is shown as $\overline{w_i}$, which is

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2} \quad (7)$$

Layer 4's output values come from the inference of rules. The result is a normalized firing rule strength-based first-order polynomial. Node function representation of the weighted output:

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_i v + q_i d + r_i), i = 1{,}2. \quad (8)$$

$O_{4,i}$ is the output, and the linear or consequent parameters are p_i, q_i and r_i.

The output layer, layer 5, adds up all the values from layer 4's input layer and converts all categorization results from fuzzy to solid values. Eq.(9) performs the averaging of all the input signals.

$$O_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i \overline{w_i} f_i}{w_1 + w_2}, i = 1{,}2. \quad (9)$$

ANFIS calculates the membership function parameters, which alter as the dataset is learned in order to keep track of the input and output data. ANFIS fine-tunes all the variables that can be changed to deal with actual circumstances. The hybrid network can be trained via a hybrid algorithm to increase convergence (Kamel and Hassan, 2009). Both a forward pass and a backward pass are parts of a hybrid learning method. Node outputs continue to advance in the forward pass up to layer 4, and the least squares algorithm helps the system identify the result. Error signals are transported backward and the premise parameters are updated by gradient descent during the backward pass (Denai et al., 2004).

3.1.4. Development of ANFIS Model

The fuzzy toolbox of MATLAB was used to model the data for the ANFIS modeling. The students' achievement grades and GPA, and their reflective thinking towards mathematical problem solving were used as the input parameters, while the single output parameter was their mathematical metacognition awareness. The ANFIS model was trained using 1000 training epochs. For the output side, the linear type of membership function (MF) was chosen, whereas the trimf type was used for the input side. The three linguistic variables Low (L), Medium (M), and High (H) were chosen as the input parameters. Of the 266 datasets, 186 datasets (or 70%) were used to train the model, and the remaining 80 datasets (or 30%) were used to test the model. Random selection was used to determine which datasets will be used to test the model.

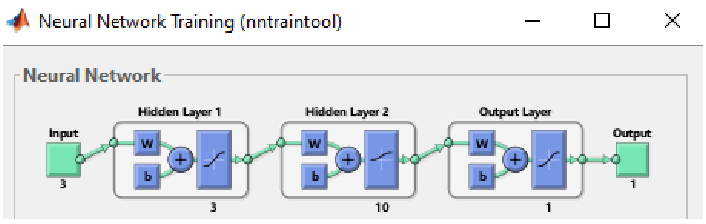
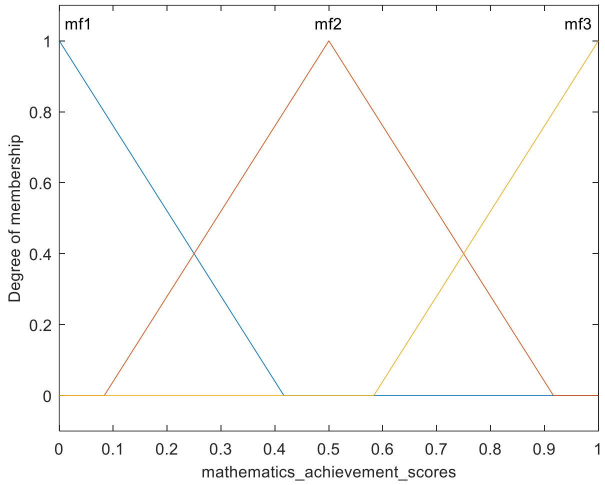
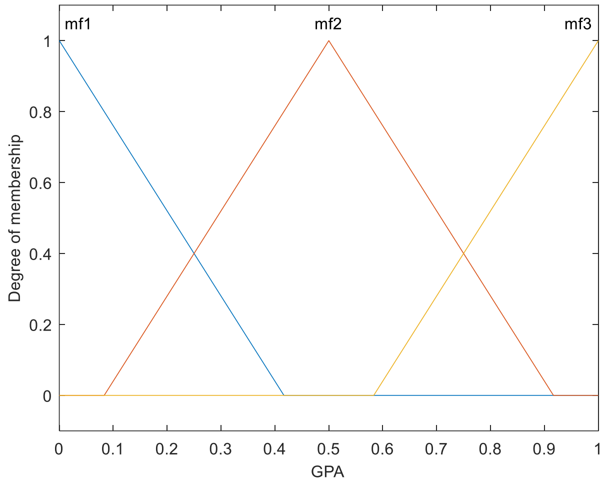
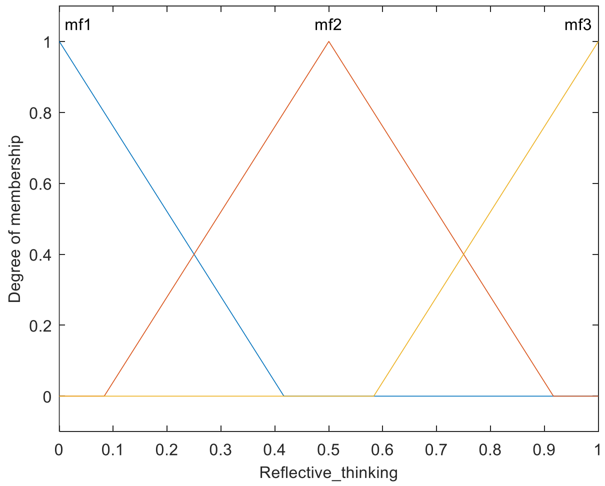


Figure 3. The proposed feed-forward NN model.

The fuzzy sets for the input variables and the output variable in the fuzzy logic model are defined as shown in Table 1. Then, all variables' membership functions are created. After testing out many types, the best type is typically selected. Figure 4 displays the proposed model's membership functions.







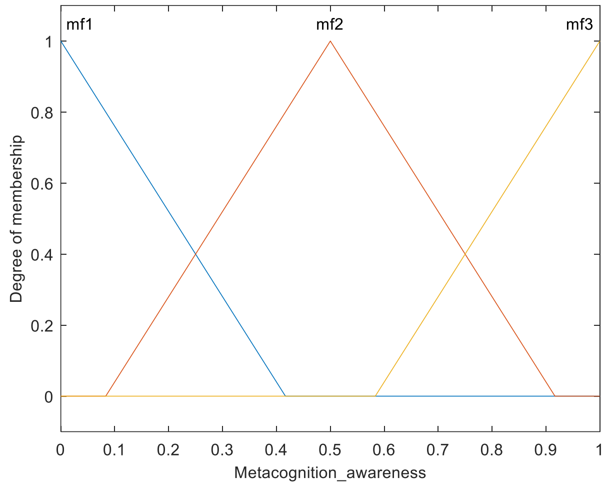


Figure 4. Membership functions.

Table 1. Fuzzy sets of the variables.

Fuzzy sets of input variables			**Fuzzy sets of the output variable**
MAS	**GPA**	**RTC**	**MMA**
Low	Low	Low	Low
Medium	Medium	Medium	Medium
High	High	High	High

***MAS: Mathematics achievement scores**
RTC: Reflective thinking characteristics
MMA: Mathematical metacognition awareness

4.2. Data Prediction by ANFIS Model

Figure 5 illustrates the fundamental architecture of the ANFIS model used in this research. The system creates 27 "and" based rule bases for three input parameters made up of three membership functions (mfs). They are then transformed into a crisp output using the same quantity of output mfs. On the other hand, the rule viewer shown in Figure 6 has shown the ANFIS model's capacity for data prediction. Within the data range, the model is capable of predicting every output value for every input parameter. The rule viewer also allows the inputs to be chosen in accordance with a specific necessary output. In reaction to the input variables (The students' achievement grades and GPA, and their reflective thinking towards mathematical problem solving), the model can predict the output data (their mathematical metacognition awareness) and vice versa. To anticipate the second parameter when one parameter changes little, the model might be modified.

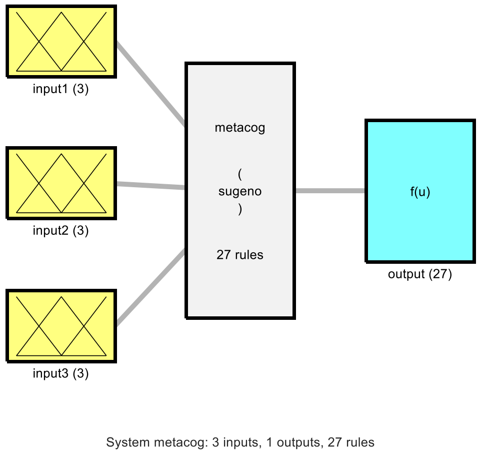


Figure 5. ANFIS model structure.

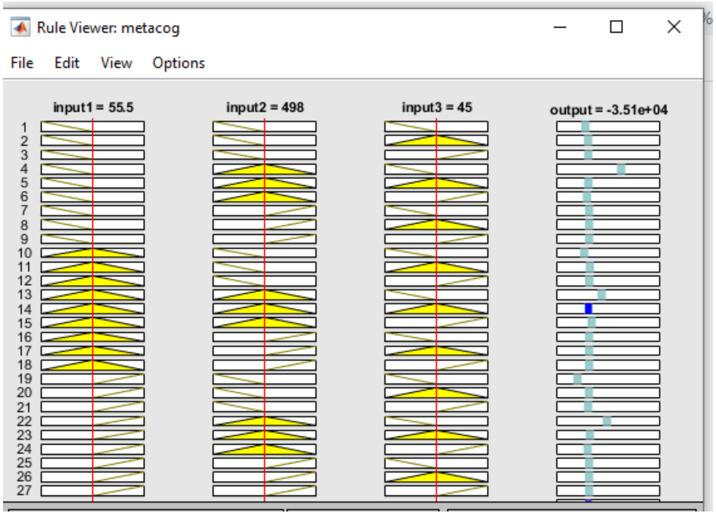


Figure 6. Rule viewer of the ANFIS prediction model.

4.3. Comparison Between Actual and Model-predicted Results

It was examined whether there was a statistically significant difference between the actual scores calculated through the students' answers to the Mathematical Metacognition Awareness Scale and the artificial scores estimated by ANN and ANFIS approaches. Paired samples t-test was used to determine the differentiation between real and artificial results. In addition, when interpreting the correlation between the results, an evaluation was made as low if the correlation coefficient is between 0.00-0.30, moderate if it is between 0.30-0.70, and high if it is between 0.70-1.00 (Büyüköztürk, 2012). All real and artificial scores are given in the AppendixPaired samples t-test was used to examine the differentiation between the real scores obtained from the scale and the artificial scores obtained with the ANFIS approach.

Table 2. Paired Samples t-test results between real scores and ANFIS scores

Metacognitive Awareness Score	N	Mean	SD	df	t	p
Real Scores	266	78.83	19.19	265	.411	.681
ANFIS Scores	266	77.64	45.96			

According to the analysis results in Table 2, there is no statistically significant difference between the real scores obtained from the scale and the artificial scores obtained with the ANFIS approach [t(265)=.411; p>.05]. This result shows that there is no difference between the artificial metacognitive awareness scores estimated by ANFIS and the real scores. Therefore, the real scores and the artificial ANFIS scores are close to each other, and the ANFIS model predicts results close to students' real metacognitive awareness scores.

Table 3. Paired Samples correlations results between real scores and ANFIS scores

	N	Correlation	Sig.
Real & ANFIS Scores	266	.155	.011

There is a statistically significant and low correlation between students' real and artificial ANFIS scores (r=.115; p<.05).

Paired samples t-test was used to examine the differentiation between the real scores obtained from the scale and the artificial scores obtained with the ANN approach.

Table 4. Paired Samples t-test results between real scores and ANN scores

Metacognitive Awareness Score	N	Mean	SD	df	t	p
Real Scores	266	78.83	19.19	265	-.173	.863
ANN Scores	266	79.00	9.29			

According to the analysis results in Table 4, there is no statistically significant difference between the real scores obtained from the scale and the artificial scores obtained with the ANN approach [t(265)=-.173 p>.05]. This result shows that there is no difference between the artificial metacognitive awareness scores estimated by ANN and the real scores. Therefore, the real scores the artificial ANN scores are close to each other, and the ANN model predicts results close to students' real metacognitive awareness scores.

Table 5. Paired Samples correlations results between real scores and ANN scores

	N	Correlation	Sig.
Real & ANN Scores	266	.499	.000

There is a statistically significant and moderate correlation between the real and artificial ANN scores of the students (r=.499; p<.05).

Paired samples t-test was used to examine the differentiation between the artificial scores obtained with the ANN and ANFIS approaches.

Table 6. Paired Samples t-test results between ANN and ANFIS scores

Metacognitive Awareness Score	N	Mean	SD	df	t	p
ANN Scores	266	79.00	9.29	265	.494	.622
ANFIS Scores	266	77.64	45.96			

According to the analysis results in Table 6, there is no statistically significant difference between the artificial scores obtained with the ANN and ANFIS approaches [t(265)=.494; p>.05]. This result shows that there is no difference between the artificial metacognitive awareness scores estimated by ANN and ANFIS approaches. Therefore, the scores obtained through ANN and ANFIS are close to each other.

Table 7. Paired Samples correlations results between ANN and ANFIS scores

	N	Correlation	Sig.
ANN & ANFIS Scores	266	.210	.001

There is a statistically significant and low correlation between the artificial ANN and ANFIS scores of the students (r=.210; p<.05).

5. Discussion and Conclusion

The research's findings not only met its main goals, but also create a new opportunity for the metacognition awareness of middle school students. The generated ANFIS, and ANN models and their comparison have demonstrated that the models are appropriate for usage in the real world. The following conclusion can be reached based on the analyses:

Metacognitive awareness scores were calculated by using ANN and ANFIS approaches, which are artificial intelligence methods, and students' mathematics achievement scores, GPA, and reflective thinking features for mathematical problem solving. These scores are not the actual scores of the students, but the scores obtained artificially by ANN and ANFIS. In this study, it is aimed to estimate the metacognitive awareness scores of students by using artificial intelligence on some of their characteristics without answering any scale. After the model extraction stages, the artificially obtained metacognitive awareness scores of the participants were reached. No research has been found on the application of ANN and ANFIS approaches, which are artificial intelligence techniques, to the field of education. However, at the end of the research, the models obtained through ANN and ANFIS for the prediction of some characteristics of students prove the main idea that artificial intelligence, which is also included in the literature, can be used to obtain tacit knowledge (Singh et al., 2012; Jagtap and Pillai, 2014).

Results from ANN and ANFIS models were compared with statistical techniques. ANN results and actual results, ANFIS results and actual results were compared in pairs. In addition, the results obtained from the ANN and ANFIS models were compared. Statistically, there is no significant difference between the students' actual metacognitive awareness scores and the predicted ANFIS and ANN metacognitive awareness scores. The average of the real and artificial metacognitive awareness scores of the students is very close to each other. Therefore, both ANN and ANFIS models predict results close to students' actual metacognitive awareness scores. What makes ANFIS different and the main reason for using it for this research is that neuro-fuzzy systems have the advantage of making it simpler than using standard neural networks because they combine ANN and fuzzy networks (Walia, 2015). The fact that there was no significant difference between the real scores and the artificial scores obtained from ANFIS in this study proves that the ANFIS approach, one of the artificial intelligence methods, gives accurate results. In the study, both selected artificial intelligence techniques were compared. The lack of significant difference between the ANFIS and ANN scores of the participants shows that artificial intelligence techniques work in harmony and give consistent results. Since reflective thinking occurs when a particular problem is perceived, reflection can best be observed in the problem-solving process (Shermis, 1992). In addition, since reflective thinking features are related to the individual's own thinking processes, it has the feature of being a predictive variable for metacognition (Aydın & Ubuz, 2010). Based on this information in the literature, the research was based on the idea that students' metacognitive awareness could be predicted through their reflective thinking features for problem solving. The fact that there is no significant difference between the real results and the artificial results at the end of the research, and that there are meaningful results in relation to it, shows that the correct variables are determined.

This research presents new results in the context of Turkey by examining the metacognitive awareness of middle school students with artificial intelligence methods. Considering the efforts to integrate artificial intelligence applications into the education system in Turkey, it is expected that knowing some characteristics of students without the need for any scale or data collection tool will bring a very different dimension to the research and education community.

6. Limitations and Future Research Directions

The only topic covered in this research is how well middle school students' mathematical metacognition awareness through academic achievement scores (mathematics and general) and reflective thinking characteristics towards mathematical problem solving. However, taking into account other characteristics would provide a clearer understanding of how the middle school students' mathematical metacognition awareness be. Additionally, working with more data enhances the ANFIS and ANN models' capacity for prediction. In addition, it may be beneficial to explore the relationships among variables that influence students' mathematical metacognition awareness (e.g., the effects of gender/grade level differences).

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Appendix

Student	Actual Score	ANFIS Score	ANN Score
S1	114	88	89
S2	93	91	91
S3	101	83	86
S4	112	112	96
S5	95	95	83
S6	83	74	81
S7	105	100	94
S8	66	74	80
S9	108	110	75
S10	89	86	90
S11	114	90	89
S12	100	88	89
S13	92	91	89
S14	88	70	74
S15	91	87	88
S16	75	74	70
S17	59	58	54
S18	89	88	95
S19	90	82	85
S20	86	80	84
S21	92	87	88
S22	80	78	78
S23	90	81	84
S24	74	87	88
S25	86	81	83
S26	102	91	90
S27	73	81	84
S28	66	69	77
S29	76	73	66
S30	49	67	72
S31	75	89	89
S32	72	79	83
S33	73	81	84
S34	69	80	76
S35	83	89	89
S36	60	57	64
S37	63	76	81
S38	90	88	84
S39	62	64	63
S40	98	95	91
S41	82	74	80
S42	91	74	81
S43	72	72	66
S44	96	91	90
S45	61	75	80
S46	65	66	63
S47	49	63	73
S48	54	75	75
S49	49	63	73
S50	74	91	92
S51	30	63	76
S52	89	78	84
S53	86	88	89
S54	85	84	82
S55	87	67	69
S56	66	70	73
S57	77	77	74
S58	85	85	87
S59	65	88	87
S60	87	75	75
S61	64	77	70
S62	80	95	96
S63	36	37	50
S64	66	70	74
S65	61	67	72
S66	102	94	92
S67	77	76	81
S68	60	73	81
S69	50	50	50
S70	39	43	72
S71	87	79	73
S72	57	69	65
S73	78	79	83
S74	103	106	108
S75	40	79	83
S76	74	78	82
S77	48	50	46
S78	53	70	73
S79	87	78	82
S80	63	89	88
S81	69	79	81
S82	52	67	70
S83	79	72	79
S84	115	93	94
S85	82	75	78
S86	67	81	73
S87	87	69	80
S88	65	76	83
S89	62	65	73
S90	77	77	70
S91	75	90	89
S92	81	75	78
S93	90	92	77
S94	62	62	61
S95	59	76	78
S96	66	68	74
S97	67	80	73
S98	91	98	91
S99	83	70	72
S100	66	66	76
S101	72	62	69
S102	85	85	77
S103	80	84	73
S104	67	68	75
S105	81	88	88

S106	92	76	72
S107	92	76	79
S108	75	77	73
S109	67	72	73
S110	99	80	76
S111	86	93	75
S112	90	75	82
S113	40	44	66
S114	58	78	85
S115	81	76	79
S116	103	80	83
S117	66	71	71
S118	100	97	76
S119	86	88	89
S120	75	89	89
S121	72	79	83
S122	73	81	84
S123	69	80	76
S124	83	89	89
S125	60	57	64
S126	63	76	81
S127	90	88	84
S128	62	64	63
S129	98	95	91
S130	82	74	80
S131	91	74	81
S132	72	72	66
S133	96	91	90
S134	61	75	80
S135	65	66	63
S136	49	63	73
S137	54	75	75
S138	49	63	73
S139	74	91	92
S140	30	63	76
S141	89	78	84
S142	86	88	89
S143	85	84	82
S144	87	67	69
S145	66	70	73
S146	77	77	74
S147	85	85	87
S148	65	88	87
S149	87	75	75
S150	84	78	85
S151	62	73	75
S152	106	91	94
S153	70	89	90
S154	84	90	91
S155	61	83	85
S156	77	76	81
S157	73	73	74
S158	93	89	90
S159	88	75	73
S160	115	90	94
S161	112	95	90
S162	102	102	91
S163	106	85	87
S164	84	68	71
S165	85	88	88
S166	81	77	81
S167	115	72	78
S168	82	75	71
S169	67	76	80

S170	69	78	82
S171	104	103	78
S172	83	78	73
S173	79	78	73
S174	79	80	77
S175	74	73	77
S176	34	33	56
S177	115	86	87
S178	65	85	76
S179	80	77	73
S180	109	75	79
S181	118	62	73
S182	93	78	74
S183	78	73	81
S184	84	99	93
S185	91	81	73
S186	111	76	81
S187	23	83	84
S188	71	104	77
S189	46	81	68
S190	86	73	80
S191	116	85	85
S192	85	-54	72
S193	113	60	74
S194	72	88	88
S195	115	79	83
S196	98	80	83
S197	106	70	77
S198	77	79	82
S199	87	85	85
S200	109	77	110
S201	104	75	74
S202	106	97	72
S203	103	93	97
S204	114	78	73
S205	115	78	73
S206	53	93	92
S207	96	79	83
S208	71	54	73
S209	100	89	86
S210	94	87	87
S211	61	78	72
S212	91	87	85
S213	115	127	96
S214	115	72	74
S215	96	77	76
S216	68	61	72
S217	110	131	96
S218	102	70	81
S219	82	83	84
S220	101	72	89
S221	94	53	78
S222	71	316	63
S223	98	88	89
S224	84	84	77
S225	97	127	95
S226	77	27	78
S227	89	71	78
S228	103	94	94
S229	64	-12	57
S230	88	243	68
S231	69	94	79
S232	48	169	59
S233	75	67	72

S234	91	94	92
S235	69	84	73
S236	67	263	73
S237	81	80	84
S238	71	75	78
S239	75	52	78
S240	66	-514	67
S241	86	94	73
S242	57	65	76
S243	43	83	74
S244	56	75	71
S245	63	61	79
S246	62	82	78
S247	55	17	76
S248	57	89	84
S249	75	7	72
S250	58	111	66
S251	59	51	75
S252	60	70	72
S253	81	75	77
S254	98	47	68
S255	52	45	71
S256	103	78	83
S257	46	70	77
S258	101	80	75
S259	70	79	71
S260	67	77	76
S261	72	75	84
S262	64	87	88
S263	59	81	74
S264	37	81	72
S265	67	96	70
S266	62	82	74