Adaptive Neuro-Fuzzy Inference System (ANFIS) Formulation to Predict Students' Neuroscience Mechanistic: A Concept of an Intelligent Model to Enhance Mathematics Learning Ability

Mohamad Ariffin Abu Bakar [1], Ahmad Termimi Ab Ghani[1], Mohd Lazim Abdullah[1], Norulhuda Ismail[2], Salmi Ab Aziz [3]

[1]*Faculty of Ocean Engineering Technology and Informatics, Universiti Malaysia Terengganu, Terengganu, Malaysia*
[2]*School of Education, Faculty of Social Sciences and Humanities, Universiti Teknologi Malaysia, Johor, Malaysia*
[3]*School of Health Sciences, Universiti Sains Malaysia (Health Campus), Kelantan, Malaysia*

***Abstract* – Students' mathematics learning ability should always be assessed, predicted and given appropriate interventions. However, due to lack of exposure and knowledge to mechanisms of neuroscience and Adaptive neuro-fuzzy inference system (ANFIS), both elements are not optimally applied in educational measurement and evaluation settings. Therefore, based on the findings of neuroscience through the AGES model and the ANFIS formulation as well as the mathematics learning model, this paper will discuss the development of a conceptual model for predicting students' neuroscience mechanistic. The significance of this model is to reveal students' mathematical learning ability and analyze the causes of weaknesses or attributes that affect learning.**

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Corresponding author: Ahmad Termimi Ab Ghani,
Faculty of Ocean Engineering Technology and Informatics, Universiti Malaysia Terengganu, Terengganu, Malaysia.
Email: mohamadariffin6299@gmail.com

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1. Introduction

Education and learning are a process of predicting the future. Uncertainty, unclear, vague and interconnected conditions between various factors make students' learning abilities difficult to determine and predict [1]. According to Do and Chen [2], efficient learning management is based on the competency to predict student achievement accurately and it is the best way in improving the quality of education services. Hwang et al. [3] pointed out that, only some educators emphasize the need to always look at the effectiveness of learning status. This means that not many educators are concerned with the assessment and analysis of students' learning abilities. This indicates that assessment of student ability is still considered light by educators, while according to Do and Chen [2], predicting student ability is the best platform to evaluate the effectiveness of teaching actions, learning activities, tutoring resources, and environmental management.

In this context, a frequently discussed issue is the gap in technology use between educators and assessment related development research in educational settings. Sri Andayani et al. [4], and Kwok et al. [5] informed that educators still use traditional methods in assessing students whereas, researchers have proven and suggested the application of computer technology provides analysis and results that are more accurate in predicting students' learning abilities. Therefore, there is a need for a method or tool in predicting student ability. Do and Chen [2] stressed that it is very important for educational institutions to implement the development of tools for predicting learning ability. Another problem discussed by Crockett, Latham, and Whitton [6] is the ability of an approach used to predict learning ability, that is, whether the methods or tools used can predict the interaction between the variables measured given that learning ability is independent of behaviour. More interesting and also important in the view of Sato-Ilic and Ilic [7] and Kwok et al. [5], which is to take into account the ability of methods and predictor tools to manipulate variables that are substantial, divergent and unclear data collection. In addition, Sri Andayani et al. [4] also stressed that data in predicting learning ability should be collected from numerical and linguistic information. Add the researcher, a method is needed to unify them to obtain the final value.

From this issue, it is clear that there is a need for the development of models and tools for predicting students' learning abilities. The best suggestion is to use a computational intelligent or machine learning approach that is from a modern mathematical formulation. The mathematical method and formulation that is often used as a predictor model is the Adaptive neuro-fuzzy inference system (ANFIS). Based on the recommendations of Do and Chen [2] and Sri Andayani et al. [4], as well as the issues discussed by Crockett, Latham and Whitton [6] above, then ANFIS is the right choice for developing a predictor model of learning ability. Research by Do and Chen [2], Hasemi et al. [8], and Stojanović et al. [1] reported that a predictor model that integrates ANFIS was successfully built and provided encouraging performance. However, research in engineering and technology integrates ANFIS more than in the social sciences [9]. Hussain Alkharusi [10] and Basaran [11] asserted, that because it is not clear and does not know how to use machine learning such as ANFIS, educational assessment faces problems in data orientation and predictive results. This can be addressed by introducing and multiplying ANFIS formulated models in educational management such as assessment and predicting learning ability.

In the context of learning, problems in learning mathematics are often discussed due to the position of the subject. Mathematics learning involves knowledge of number coordination, shapes, reasoning, decision making and problem-solving [12] and is highly influential on current scientific and technological advances [1]. Mathematics is made a core subject that should be mastered by all students in the education curriculum of each country [13]. Mathematics learning is also used as a measure of the performance of the education system, which is evidence to determine the level of teaching quality and student development at the international level such as Trend in Science and Mathematics Study (TIMSS) and Program for International Student Assessment (PISA) [13], [14]. This polemic has made mathematics education and assessment of student ability very important. Therefore, the factors or attributes that are the backbone of mathematics learning need to be studied in depth.

Several studies in the last five years still show that the level of mathematics learning is low [15], [16]. Among the attributes described as influences in determining and predicting mathematics, learning ability is emotion [17], readiness [18], [19], motivation [20], metacognitive coordination [21], memory [22], [23] and mathematical problem-solving mechanisms [24], [25]. To overcome this situation, a detailed study of the attributes involved is required and should be conducted based on internal and external aspects.

A rough view shows the internal attributes revolve around the psychological, behavioural and cognitive levels of the students. So, backing up this problem is new knowledge and findings of neuroscience and learning as suggested by Alghafri and Ismail [23]. According to Alghafri and Ismail [23], neuroscience mechanisms play an important role during mathematics learning i.e., influencing students' emotions, actions and thinking coordination. There is a knowledge gap between neuroscience and its impact on students' learning abilities [26], [27]. Hohnen and Murphy [20] pointed out that the failures of educators in producing effective interventions are due to not knowing the role, nature and potential of certain components and parts of the brain involved in learning. In practice, there is still a lack of research in the field of neuroscience of learning [27]. Neuroscience studies are more focused on brain growth problems, autism spectrum disorder (ASD) and also learning problems such as dyslexia, anxiety, number literacy problems and so on [25]. Technological-assisted diagnostic studies such as electroencephalography (EEG), positron emission topography (PET) and functional magnetic resonance imaging (fMRI) have preceded the development of neuroscience studies over normal learning problems [24]. This situation suggests that educational researchers do not take the opportunity to delve into the mechanisms of neuroscience that are more synonymous with effective learning, especially in analyzing the potential and mechanistic functions of specific brain parts [21], [22].

The external aspect is from a technical point of view and tools to assess and analyze the attributes of mathematics ability. As discussed earlier, there is a gap in the practical application of machine learning and assessment of learning. According to Kwok et al. [5] and Hussain Alkharusi [10] educators still fail to evaluate learning outcomes because they are not implemented using the latest approaches such as fuzzy analytics or multi-criteria decision making. To overcome the issue of accuracy in selecting appropriate assessment methods and tools, further research is needed in evaluating the applicability of machine learning approaches in educational assessment. Based on the discussion, there is a triangulation of study gaps, i.e., the need for ANFIS formulation in predicting attributes, the influence of neuroscience mechanistic in learning and the level of mathematics learning ability of students. Therefore, a study and concept model of neuroscience mechanistic predictor formulated by ANFIS in determining the level of mathematical learning ability needs to be developed. This predictor concept model will be used by educators to assess in-depth the level of mathematics learning ability and look at the weighting of any attributes that exert a strong influence. So, the objective of this paper is to develop an ANFIS formulated conceptual model to predict students' neuroscience mechanistic. To that end, the next section in this paper will describe the knowledge of neuroscience mechanistic as well as its relevance to mathematics learning ability. Followed by the conceptual design of the model that will be developed by detailing the ANFIS system, neuroscience mechanistic and mathematics learning models. Then, the researchers detailed the formulation of ANFIS in the development of the model introduced which is the *Intelligent ANFIS Neuro-mechanistic Learning Model*.

2. Neuroscience Mechanistic and Mathematics Learning Ability

Neuroscience is a multidisciplinary and rapidly evolving field of knowledge [23], [26], which is about the functionality of certain parts of the brain associated with behaviour, thinking, and human learning to acquire understanding and knowledge [20]. Neuroscience research is largely focused on the study of brain performance during the thought process, the range or potential of thinking to produce knowledge, and shape attitudes and behaviours [21]. The human brain can adapt functions and structures according to whatever situation is referred to as a mechanism or if related to the process of action and time, neuroscience mechanistic is used [26]. There are also other frequently used terms such as brain mechanism [28] and neural mechanism [22]. Zeithamova et al. [28] pointed out that there are differences in mechanisms depending on the category of the particular part of the brain which will form different outcomes or purposes. Thus, neuroscience mechanistic refers to how and when brain processes work and function to produce certain effects such as movement, emotion, thinking, learning, remembering and also includes all controlled and uncontrolled actions.

Based on the theories of Educational Neuroscience (EN), Mind, Brain and Education (MBE), and Neuropedagogy, neuroscience knowledge is explored and shows potential in understanding individual learning abilities [25], [29]. The studies of Hohnen and Murphy [20] show that changes in the individual brain in terms of anatomy, properties, roles, mechanisms and neural functionality occur during learning. Amran and Bakar [24] reported a significant relationship that resulted between children's early mathematical skills and the rate at which neuroplasticity occurs that alters the cortical anatomical surface. [26]. De Smedt et al. [26] in turn showed a correlation between differences in students' behaviour while understanding new mathematics concepts and activities that occur on the prefrontal when students are exposed to new concepts. The effects or nature of neuroplasticity have greatly altered the assumptions and myths that brain skills and intelligence are "fixed" or static [25], [28]. The true potential of individuals in learning is closely related to the rate of nerve connection, activation, regulation, attention and experience.

When mathematics learning begins, neural circuits are formed through synaptic connections by the neurotransmitter dopamine, a brain chemical [25], [29]. The resulting circuit will be faster, smoother and more efficient when there is repetition (drill) that is through the process of myelination [29]. Frequent myelination will expand the contact area (region) that is the development of plasticity [28]. However, according to Willis [29] learning is in the form of action, for example, if a mathematics problem is successfully solved, it will activate the reward system (circuit) where more dopamine will be produced and will increase nerves connected. This effect will increase students' motivation, attention and focus. The system (circuit) that has been set earlier will be tested for safety (comfort) levels based on the current situation or experience by the amygdala filter [20]. Next, the regulation circuit will form the pathways, processes and actions of thinking (regulation circuit) [22]. Metacognitive ability will be influenced by executive functions on the frontal lobes that are through high-level thinking circuits that involve decision-making, comparison and analysis [28]. It is at this stage that the learning of mathematics concepts and problem-solving will be perfected based on mechanistic and subsequently form temporary memory or permanent memory [19].

3. Conceptual Framework of Intelligent ANFIS Model to Predict Students' Neuroscience Mechanistic

3.1. ANFIS System for the Prediction Model

Adaptive neuro-fuzzy inference system (ANFIS) is a method related to coordinating research data, and was proposed by J.S. Roger Jang [11]. This method is a hybrid combination between neural networks and fuzzy logic by way of grouping values in a fuzzy set [2]. The ANFIS method is an efficient predictor model based on results with a low error rate. Moreover, according to Chopra et al. [9], the level of accuracy of the ANFIS model is influenced by the number and quality of data samples. However, it can be handled with nonlinear data within an error.

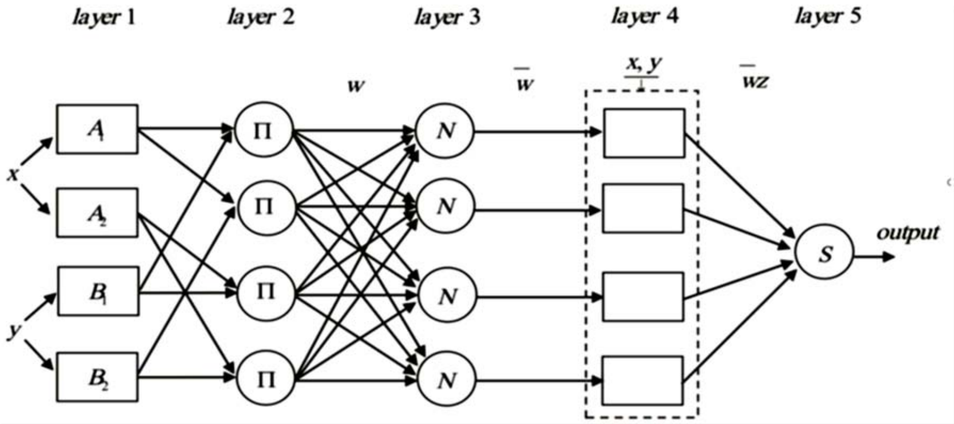

Figure 1. The architecture of the general ANFIS System

The overall equation of the ANFIS model can be determined as follow:

$$Rule\ 1 : if\ x\ is\ A_1\ and\ y\ is\ B_1\ then$$
$$z_1 = p_1x + q_1y + r_1$$
$$Rule\ 2 : if\ x\ is\ A_1\ and\ y\ is\ B_2\ then$$
$$z_2 = p_2x + q_2y + r_2$$
$$Rule\ 3 : if\ x\ is\ A_2\ and\ y\ is\ B_1\ then$$
$$z_3 = p_3x + q_3y + r_3$$
$$Rule\ 4 : if\ x\ is\ A_2\ and\ y\ is\ B_2\ then$$
$$z_4 = p_4x + q_4y + r_4 \qquad (1)$$

Where x and y are inputs, and z is output, A_i and B_i (i =1,2,3,4) are the fuzzy sets, p_i, q_i and r_i (i =1,2,3,4) are the design parameters that are determined during the training process. In general, as shown in Figure 1., the architecture of ANFIS includes five layers of interconnected neurons [2], [9]. Each of these layers functions a different task during the computation process, namely, the fuzzification layer, the rule layer, the normalization layer, the defuzzification layer, and a single summation node. The forecasting process by ANFIS begins with the determination and inclusion of a sample of data with input and output variables.

Layer 1: Known as input nodes, where each neuron is an adaptive nodes layer. Receives the crisp inputs and converts them into the fuzzy value by membership functions, as follows:

$$O_i^1 = \mu_{A_i}(x) \qquad i = 1,2$$

$$O_i^1 = \mu_{B_{i-2}}(x) \qquad i = 3,4 \qquad (2)$$

where O_i^1 is output from node i and μ is a membership function.

Layer 2: Also called the membership layer, represents the layer in which the fuzzification is performed. Each node in the second layer is considered a fixed node labelled *Π*. The AND operator is implemented to achieve an output that gives the result of the before that rule. According to Chopra et al. [9], this layer is the implication process, where the neurons contain the product of inputs, based on the weight of premise parameters. The output of the kth node (w_k) is defined as:

$$O_k^2 = w_k = \mu_{A_i}(x)\mu_{B_j}(x)$$
$$i = 1,2 \quad j = 1,2 \quad k = 1,2,3,4 \qquad (3)$$

Layer 3: Average nodes layer. Each node in this layer is a fixed node labelled *N*. The function of this layer is the calculation of the ratio of the i_{th} rule's firing strength in the second layer. The outputs of this layer ($\overline{w_i}$) are called normalized firing strengths (weight of the neuron), and can be computed as:

$$O_i^3 = \overline{w_i} = \frac{w_i}{\sum_{i=1}^{4} w_k} \quad i = 1,2,3,4 \qquad (4)$$

Layer 4: This is the defuzzification layer or consequent nodes layer. In this layer, the contribution of each i_{th} rule to the total output is computed. The output of each node in this layer is simply the product of the normalized firing strength and a first-order Sugeno model. Thus, the outputs of the fourth layer can be defined as:

$$O_i^4 = \overline{w_i} z_i = \overline{w_i}(p_i x + q_i y + r_i) \quad i = 1,2,3,4 \tag{5}$$

Layer 5: Output nodes layer. In this layer, there is only a single neuron present for output with a fixed node labelled *S*. The task of the fifth layer is a summation of all incoming signals. Hence, the final output of the ANFIS model is given by:

$$O_i^5 = \sum_{i=1}^4 \overline{w_i}\, z_i \tag{6}$$

The ANFIS is then trained by a training algorithm to learn the knowledge from the attached data. When the ANFIS model is trained, the trained model could be used to make a prediction for the unknown input variable or to rank the input variables depending on their influence on the output variable. To determine and improve the performance of the best-constructed model, various values for significant model parameters were tested based on a trial-and-error analysis. Finally, for each model, the best-resulted output with the minimum estimation error was determined based on the coefficient of determination (R^2), Root Mean Square Error (*RMSE*), and Mean Bias Error (*MBE*) as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \widehat{y_i})^2}{\sum_{i=1}^n (y_i - \widehat{y_i})^2} \; (0 \le R^2 \le 1) \tag{7}$$

$$RMSE = \sqrt{(\sum_{i=1}^n (y_i - \widehat{y_i})^2)\frac{}{n}} (0 \le RMSE \le +\infty) \tag{8}$$

$$MBE = 1/n \sum_{i=1}^n (y_i - \widehat{y_i}) \; (-1 \le MBE \le +1) \tag{9}$$

3.2. AGES Model of Neuroscience Mechanistic

Mathematics learning is influenced by the strength and ability of certain parts of the brain to act and function optimally. The management of physical, cognitive and affective learning plays an important role in ensuring effective mathematics learning because these constructs interact with each other based on the students' level of neuroscience mechanistic [31], [32]. Physical aspects such as interesting learning materials, conducive environment, innovative delivery and so on, can stimulate student motivation and engagement. Cognitive aspects such as focus, memory, regulation of thinking and computational work form mastery of mathematics concepts and problem-solving. The affective value of learning also ensures that students remain interested and able to produce meaningful experiences. Davachi et al. [30] have introduced 4 elements that are the motivators of individual actions to achieve goals Attention, Generation, Emotion and Spacing which are based on mechanisms that occur in the parts, properties and functions of the brain. Learning is also an individual action to achieve a goal, so this element is also very significant in driving students' mathematics learning. Dimensions and premises that show cognitive, psychological and behavioural practices or actions in those elements can be used as objects and criteria to measure students' mathematics learning ability.

Table 1. Element of AGES model (Davachi et al.,2010)

Attention	Demonstrates behaviours in which one is paying attention, alerts and provides focus to the learning environment. Motivated, mentally and physically ready to learn and can perform thinking activities.
Generation	Students have high confidence to learn, set clear objectives, know the purpose of learning and know-how to learn. Design and select learning strategies. Can construct abstracts and overviews of learning. Regulate cognitively and practice level thinking practices. Implement strategies that can operate mathematical calculations. Constantly monitor the understanding and completeness of learning.
Emotion	Build personal value and form a sense of belonging to learning. Positive thinking can control emotions and create excitement. Stimulate the mind by aiming for pleasure in success (self-reward).
Spacing	Associate current learning with past knowledge and success. structuring memory and building ways to strengthen memory such as building acronyms, diagrams, sentences and so on. Manage time well for periods of repetition, remembering and drills

Based on the elements of the AGES model specified in Table 1., effective mathematics learning occurs when students should have maximum attention with a greater focus and motivation, ensuring one focus during learning events, and utilizing more novelty and change during learning experiences. Encouraging a significant generation of learning by students when learning new mathematics concepts to build their ownership. A positive emotional environment with opportunities for students to gain positive feedback and connect deeply with peers. Students utilise more spacing of learning instead of massing and repetition, with more dispersed content.

3.3. Mathematics Learning Model

According to Schoenfeld [31], the priority in the mathematics curriculum is the understanding of concepts and the ability to solve problems as well as the application of knowledge. Mathematics learning ability will be at an optimal level when students successfully apply mathematics concepts and can solve problems perfectly [28]. Neurocognitive studies show that concept mastery and problem-solving abilities are significant to the neuroscience mechanics triggered during learning [24]. Based on Mayer's Model [12], students' actions to understand concepts and solve mathematics problems are based on four components that lead to the thinking process and mechanics of neuroscience, namely, Translation, Interpretation, Planning, and Execution. This component is also in line with Schoenfeld's theory of mathematics learning, which describes the process of mathematics learning as a mental discipline that trains the cognitive (mind) to turn students into trained thinkers [31]. [27]. Corrado Matta [27] argue that the process of mathematics learning is a process of integration and mechanism of cognitive activity in general and a deep cognitive process. Mayer [12] introduces a model of mathematics learning and problem-solving strategies to act as a moderator for learning mastery through the following four components described in Table 2.:

Table 2. Component of Mayers' (2003) mathematics learning model

Translation	Students will use the senses to understand situations (tasks) and give meaning. Reading, examining pictures, diagrams, graphs, symbols, etc., are implemented to define the concepts and problems revealed. Students will find meaning in the instructions and structure of the task.
Interpretation	Follow-up action after understanding each word, symbol or diagram. The onset of deep and complex cognitive processes. There will be the detection of letters and digits in parts of the brain, including parts such as the frontal, occipital, temporal and left inferior temporal gyrus (ITG). This mechanism is an appreciation of the problem situation (task) that students begin to build theory and knowledge. Students research what to learn and how to achieve that goal.
Planning	Depends on the students' thinking and decision-making skills to determine which strategies are appropriate for the current learning goals. Teachers ensure the right strategy and encourage students to choose the right strategy. This component is a tendency for students to see for themselves the learning process and to ensure that strategies are implemented correctly and can continue to be applied.
Execution	The ability of students to ensure learning is on the right track by continuing to provide alternative contexts or strategies in the event of a possible difference from the actual goal of the assignment or learning.

4. Formulation of ANFIS System for Design of the Intelligent Model to Predict Students' Neuroscience Mechanistic

The concept of the intelligent model to predict students' neuroscience mechanistic is based on AGES and mathematics learning models integrated into the ANFIS of developing parameters (fuzzy scale) that will meet the needs of mathematics learning ability assessment. Students' mathematics learning abilities are fuzzy, complex, interconnected between various factors and the form of assessment also involves large data. The ability to learn mathematics is influenced by the strength and ability of students to regulate and manage the psychological, behavioural and cognitive elements that are included in the components of neuroscience mechanisms. These measurements can be determined using specific attributes and parameters. Integration between predictor models through computational intelligence approaches, mechanistic neuroscience models and mathematics learning models is needed to form a new model that can be practised as an alternative assessment to determine students' mathematical learning abilities. This model is named as Intelligent ANFIS Neuro-mechanistic Learning Model. The operational design of developing and architecture of the model is shown in Figure 2. as follows.

The first step of ANFIS model formulation is done by finalising the attribute and parameter as inputs and outputs variables setting into a structure of the model based on AGES and mathematic learning models, described in Table 3.

Table 3. The proposed attribute in the intelligent model to predict students' neuroscience mechanistic

AGES model (Davachi et al., 2010)	**Mathematic learning model (Mayer, 2003)**	***Intelligent ANFIS neuro-mechanistic learning model***	**Description**
		Motivation	This attribute indicates the level of interest, enjoyment and inclination of students to mathematics. Can generate self-motivation. Have positive self-belief and high confidence in managing learning.
Attention	Translation	Attention	Reflection on behaviours that show readiness and focus on learning. Know and have information about learning resources (mathematics topics). Be aware of the abilities and achievements of the brain and memory.
Generation	Interpretation	Activation	Competently formulates learning objectives and can draw early conclusions about learning. Can construct abstracts and overviews of learning. Know how to stimulate and the need to think according to the level of learning. Able to construct mathematics operation sentences from assignment sources. Specify the formula or mathematics formula to be used.
Generation	Planning	Regulation	Build a learning arrangement circuit by planning mathematics operations, choosing solution strategies and allocating time. Able to regulate thinking activities. Control the depth of thinking according to the level of difficulty of the mathematics task. Build relationships between previous mathematics concepts and existing knowledge with current mathematics learning.
Emotion	Execution	Implementation	Perform mathematics operations accurately and effectively. Have a specific strategy and monitor accuracy and completeness. Efficiently adopt alternative solutions if experiencing problems. Always positive with accomplishments, able to control emotions and not easily confused
Spacing		Evaluation	Ensure the solution is accurate. Evaluate calculations utilizing repetition or looking back. Compare current learning findings with previous experience. Create similar solutions to ensure accuracy.

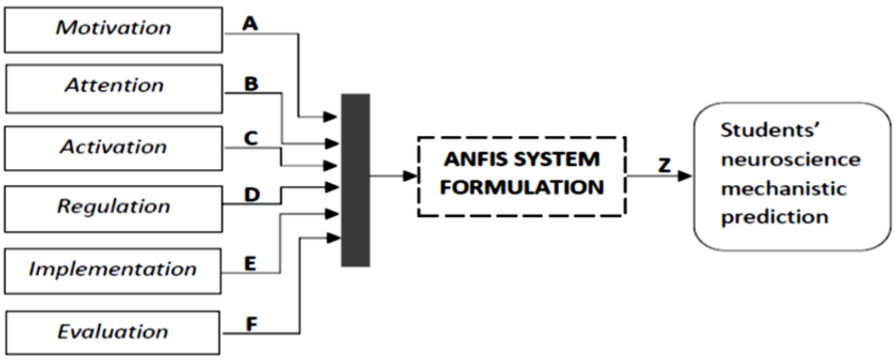

Figure 2. Architecture of proposed Intelligent ANFIS neuro-mechanistic learning model

The second is the fuzzification step. The fuzzification interface transforms the crisp inputs into truth values and the rule base is characterized in the form of "if-then rules" in which the antecedents and consequents involve linguistic variables. In this model, we propose very poor, poor, average, above average, good, very good and excellent as the linguistic variable as listed in Table 4., to predict students' neuroscience mechanistic in terms of mathematics learning cluster (level).

Table 4. Linguistic variables

Linguistic Terms	**Triangular Fuzzy Value**
Very poor	(0.00,0.00,0.17)
Poor	(0.00, 0.17, 0.33)
Average	(0.17, 0.33, 0.50)
Above average	(0.33, 0.50, 0.67)
Good	(0.50, 0.67, 0.83)
Very good	(0.67, 0.83, 1.00)
Excellent	(0.83,1.00,1.00)

The fuzzy rule (or fuzzy if-then rule) form is as follows:

Rule 1: If Motivation is in Excellent and Attention is in Excellent and Activation is in Excellent and Regulation is in Excellent and Implementation is in Excellent and Evaluation is in Excellent then students' neuroscience mechanistic is in Excellent.

Rule 2: If Motivation is in Very good and Attention is in Very good and … Evaluation is Very good then students' neuroscience mechanistic is in Very good.

Rule 3: If Motivation is in Good and Attention is in Good and … Evaluation is Good then students' neuroscience mechanistic is in Good.

Rule 4: If Motivation is Above average and Attention is in Above average and … Evaluation is Above average then students' neuroscience mechanistic is in Above average.

Rule 5: If Motivation is in Average and Attention is in Average and … Evaluation is Average then students' neuroscience mechanistic is in Average.

Rule 6: If Motivation is in Poor and Attention is in Poor and … Evaluation is Poor then students' neuroscience mechanistic is in Poor.

Rule 7: If Motivation is in Very poor and Attention is in Very poor and … Evaluation is Very poor then students' neuroscience mechanistic is in Very poor.

The weight of premise parameters or the node output is calculated as follows:

$$O_i^2 = w_i = \mu_{A_i}(Mot).\mu_{B_i}(Att) \dots \mu_{F_i}(Eva),\quad i = 1,2,3,\dots \tag{10}$$

Next, the premise parameters are fixed and normalized by the sum of weights of all parameters. The node output is calculated as follows:

$$O_i^3 = \overline{w_i} = \frac{w_i}{\sum w_i},\qquad i = 1,2,3,\dots \tag{11}$$

Next is the defuzzification interface. Defuzzification layer where each parameter is adaptive and holds the consequent parameters of the architecture. The node output is calculated as follows:

$$O_i^4 = \overline{w_i} z_i = \overline{w_i}\,.(a_i A + b_i B + d_i D + e_i E + f_i F + r_i),\qquad i = 1,2,3,\dots. \tag{12}$$

Then, the output layer where a single neuron is present for students' neuroscience mechanistic (output), which is the sum of all the attributes (inputs). The node output is calculated as follows:

$$O_i^5 = z\,(A,B,C,D,E,F) = \sum_i \overline{w_i} z_i = \frac{\sum_i w_i z_i}{\sum_i w_i},\quad i = 1,2,3,\dots. \tag{13}$$

Validation experiments were performed, and the neuroscience's mechanistic and mathematics learning attribute factors optimized by the Intelligent ANFIS neuro-mechanistic learning model were tested to evaluate the efficiency of the model for modelling and optimizing the students' neuroscience mechanistic in terms of clustering mathematics learning ability. Finally, the best-resulted output with the minimum estimation error was determined based on the coefficient of determination (R^2), Root Mean Square Error (*RMSE*), and Mean Bias Error (*MBE*) using equation (7), (8) and (9). Next, the hypotheses will be tested to see if each attribute is significant to the students' neuroscience mechanistic in mathematics learning.

5. Conclusion

This study describes the development of a conceptual model, in which the ANFIS formulation is integrated into a predictive model of students' neuroscience mechanistic aimed at clustering mathematics learning ability. Neuroscience mechanisms are taken into account in determining students' ability to form meaningful mathematics learning. This field of knowledge is explored on the basis that the tendency of mathematics learning involves the activities of the mind, brain, and memory, and even involves psychological and behavioural components that are directly related to neuroscience. The high need and validity of predictor models developed based on machine learning applications such as the ANFIS system also motivates and becomes the backbone of this conceptual model introduced. Conceptually this model can be used by educators to cluster learning abilities and subsequently provide appropriate interventions. However, it is also significant in predicting a student's ability for streaming purposes and so on. So, for the integrity of this conceptual model, it needs to be followed by further studies especially in producing real models. In addition, it is recommended that this study be extended to the development of other models in educational assessment, or to integrate other methods such as DEMATEL, ANN, TOPSIS and so on.

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