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The ANFIS Model Approach in Classifying the Characteristics of Children with Special Needs at SLB in Southwest Papua

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Abstract: Special Elementary Education (SDLB) has a strategic role in providing equal access to education for Children with Special Needs (ABK). Observations at one of the Special Needs schools (SLB) in Southwest Papua show that the initial assessment process of ABK characteristics based on age, IQ, and motor skills has not been effective. This study aims to develop a system based on the Adaptive Neuro-Fuzzy Inference System (ANFIS) model to assist the initial classification process of ABK characteristics and support initial assessments at school. The ANFIS model is used to study the nonlinear relationship between input variables and classification results. Testing is carried out using validated data to assess the level of accuracy and consistency of the model. The results show that the ANFIS model-based system has an accuracy level of 85.7% with stable predictive capabilities on most of the test data. These findings show that the integration of ANFIS into a web-based system can be an effective tool for teachers in conducting initial assessments, so that the process of identifying ABK characteristics can be carried out more quickly, objectively, and efficiently.

Keywords: ANFIS; ABK; Characteristics of Children; Classifying; SLB

Introduction

Special Elementary Education (SDLB) has a strategic role in the inclusive education system to create equal learning opportunities for children with special needs (ABK) (Ahmadiham et al., 2020; Murwati & Syefriani, 2024). Special schools have a responsibility to identify the characteristics, abilities and learning needs of each student so that the learning process can be optimally adapted (Pratama et al., 2024; Sari et al., 2025; Wulayalin & Suprihatiningrum, 2024). However, the implementation of the assessment process for children with special needs (ABK) still relies on manual and subjective teacher observations. This can lead to inconsistencies in assessment results between students and across periods.

Initial observations at a special needs school in Southwest Papua revealed challenges in classifying student characteristics based on initial data collected, such as age, IQ level, and motor skills. Teachers experienced difficulty quickly and accurately determining student development categories. This situation necessitates an expert system-based technological approach capable of flexibly integrating quantitative and qualitative data.

According to Nisa et al. (2025); Widoningrum et al. (2025) The characteristics of children with special needs include limitations in physical, intellectual, emotional and social aspects. According to Imam et al. (2024) physical characteristics relate to body conditions such as stiffness and paralysis. According to Bactiar et al. (2024) explains the emotional characteristics of ABK including difficulty in recognizing and expressing emotions and lack of empathy, and uncontrolled behavior. Meanwhile, according to Maharani et al. (2024) hearing characteristics are individuals who have hearing impairments, either permanent or temporary. While Khoirunisa et al. (2024) adding that the characteristics of vision are related to

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visual impairments that require special education services (Rabiasa et al., 2024).

The diversity of these characteristics indicates that each special needs child has a unique ability profile, so the identification and classification process cannot be carried out in a general or uniform manner. An approach capable of processing quantitative data including age, IQ, and motor skills is required. Expert systems are an effective alternative to assist teachers in conducting initial assessments to determine the ease and accuracy of classifying special needs children quickly and consistently (Alam et al., 2024; Ermin Ermin, 2023; Esmaili et al., 2021).

One of the appropriate methods for handling decision making is to use the Adaptive Neuro-Fuzzy Inference System (ANFIS) model, which is the right choice because it is able to combine the advantages of fuzzy logic in handling uncertain data with the capabilities of artificial neural networks in flexible learning processes (Bazrafshan et al., 2022; Ermin, 2023; Febrian et al., 2022).

The ANFIS model is able to adjust weights and parameters based on training data and can improve classification accuracy through an adaptive and continuous inference process (Al Sudani & Salem, 2022; Mutiah et al., 2024; Sugiharto et al., 2023). Thus, the use of the ANFIS method is expected to help classify children with special needs according to their characteristics in a more objective and efficient manner (A & Iksan,2025; Ishak et al., 2024; Kumari et al., 2025).

The novelty of this research lies in the use of the ANFIS method integrated into an expert system to classify the characteristics of children with special needs based on three main variables: age, IQ, and motor skills. This integration is designed to facilitate teachers in conducting assessments automatically without requiring in-depth technical knowledge, and is tailored to the conditions of special needs schools (SLB) in Southwest Papua Province (’Aini & Ratnaningrum, 2025; Muzakki et al., 2025; Yaseen et al., 2020).

Method

Types and approaches of research

This study uses an experimental quantitative approach by applying the Adaptive Neuro-Fuzzy Inference System (ANFIS) as a method for classifying children with special needs (ABK) (Mosavi et al., 2019). The use of the ANFIS model in this study is due to its ability to combine fuzzy logic in handling uncertainty and the ability of artificial neural networks to carry out flexible learning processes (Adnan Ikram et al., 2022; Akbar et al., 2025; Nugraha et al., 2021).

Research Data and Variables

The research data was obtained from observations and interviews with teachers and experts at special schools (SLB) in Southwest Papua. The data collected consisted of three input and output variables (Kiswanto et al., 2022; Zhang et al., 2021). The input variables are: Child's Age, IQ Score (Guidance and Counseling assessment results), and Motor Skills (observation results from the accompanying teacher). The output variable is the result of the classification of child characteristics, namely the learning ability categories of children with special needs, which consist of three levels: category 1: high ability, category 2: medium ability, and category 3: low ability. Each input data is processed to produce a prediction of the characteristics category of children with special needs based on the pattern of needs between variables (Ikram et al., 2022).

Data Collection Procedures

Data collection was conducted in two stages: interviews and observations with class teachers and guidance counselors to obtain qualitative data on the children's conditions. The instruments, consisting of observation sheets and questionnaires, were validated by special education experts according to the assessment indicators. The data were then converted into numerical form for processing in the ANFIS model (Ahmadi & Moradinia, 2024; Aiza et al., 2025).

ANFIS Model Stages

The ANFIS model is used to classify the characteristics of children with special needs based on input data of age (x_1), IQ (x_2) and motor skills (x_3) as input. A_1, B_1, C_1 are fuzzy sets that represent the categories of each input, such as low, medium and high. The ANFIS structure design, namely the fuzzy membership function is determined using the Gaussian Membership Function and the ANFIS architecture consists of five layers (Almunawar et al., 2024; M. Khalaf, 2020; Sinaga et al., 2024).

Layer 1 (Fuzzification): each node in this layer is adaptive, and functions to calculate the membership level of each input against its fuzzy set.

$$O_i^1 = \mu_{A_i}(x), \quad i = 1,2,3 \tag{1}$$

Layer 2 (Fuzzy Rules): All nodes in this layer are fixed and are denoted by the symbol Π which indicates that the node performs a simple multiplication operation.

$$O_i^2 = \mu_{A_i}(x_1).\mu_{B_i}(x_2).\mu_{Ci}(x_3) \quad i = 1,2 \tag{2}$$

Value of O_i^2 is the activation strength of fuzzy rules based on a combination of age, IQ, and motor skills.

Layer 3 (normalization): All nodes in this layer are also fixed and are denoted by the symbol N, which indicates that the node functions to normalize the firing strength from the previous layer.

$$O_i^3 = w_i = \frac{w_i}{\Sigma_j w_j} \tag{3}$$

This normalization ensures that the total weight of the rules is 1.

Layer 4 (Normalization): In this layer, the nodes are adaptive, with the output of each node being a simple product of the normalized firing strength and a first-order polynomial (a first-order Sugeno model).

$$O_i^4 = w_i f_i = w_i(p_i x_1 + q_i x_2 + r_i x_3 + s_i) \tag{4}$$

The parameters pi, qi, ri, and si are known as consequent parameters, which are updated during the training process to adapt the ACF data pattern model.

Layer 5 (defuzzification/output): There is one fixed node labeled Σ, where all input signals are summed at this node.

$$O_i^5 = \Sigma_i w_i f_i = \frac{\Sigma_i w_i f_i}{\Sigma_i w_i} \tag{5}$$

The final value O_i^5 The results of the classification of ABK characteristics.

Model Training

The trained data is fed into the model using a hybrid learning algorithm, a combination of the Least Squares Estimation (LSE) and Backpropagation (BP) methods (Arifuddin et al., 2025).

Model Validation

The model is tested using separate test data to measure the classification accuracy level. Evaluation is carried out by calculating the classification accuracy value (Buhungo et al., 2024; Ratnasari et al., 2023).

Result and Discussion

This section presents the results of data processing and analysis of research conducted to classify the characteristics of children with special needs at the Special Needs School in Southwest Papua using the Adaptive Neuro-Fuzzy Inference System (ANFIS) method. The analysis process began with the collection and preparation of initial data, followed by preprocessing, membership function design, model training, and system testing. The results were then compared with the target data to assess the system's accuracy. The initial data used as the basis for the analysis can be seen in Table 1.

Table 1. Initial Data

Faction	Age	IQ	Motoric	Type of ABK (target)
1	9	80	7	Deafness
2	9	120	5	Blindness
3	2	100	2	Paralysis
4	9	85	4	Mental Retardation
5	7	95	6	Autism
6	10	110	5	Mental Retardation
7	8	80	5	Autism

Table 1 presents the initial data that serves as the basis for the classification process for children with special needs (ABK) using the ANFIS method. The data consists of seven samples with attributes such as Fraction, Age, IQ, and Motor Skills, and the type of ABK as the classification target. Ages ranged from 2 to 10 years, with IQ levels ranging from 80–120 and motor skills ranging from 4–7. The target ABK categories included deafness, blindness, paralysis, intellectual disability, and autism, reflecting the diverse characteristics of students as important input for the training and testing of the classification model.

Membership Function (MF) Assumptions

For each input variable, we defined three triangular fuzzy sets: Low (R), Medium (S), and High (T). With consequences in the form of integer constants (which are later mapped to the ABK class), as in the rule base in Table 2.

Table 2. Rule Base

Code	IF age & IQ & Motoric	THEN Constanta (z)
R1	High Age AND IQ Low AND High Motor Skills	1 = Deaf
R2	High Age AND High IQ AND Moderate Motor Skills	2 = Blind
R3	Low Age AND Medium IQ AND Low Motor Skills	3 = Paralysis
R4	High Age AND Low IQ AND Moderate Motor Skills	4 = Mental Retardation
R5	Middle Age AND Moderate IQ AND Moderate Motor Skills	5 = Autism

Table 2 displays the rule base used as the basis for decision-making in the ANFIS classification system. Each rule (R1–R5) combines the conditions of Age, IQ, and Motor Skills with fuzzy logic to determine an output constant (z) that represents the type of child with special needs. For example, R1 specifies that if a child's age is high, IQ is low, and motor skills are high, it is predicted as Deaf (z=1), while R5 indicates that if a child's age is medium, IQ is medium, and motor skills are predicted as Autistic (z=5). These rules form an important foundation in the inference process to classify each data set according to its characteristics.

Degree of Membership

The degree of membership calculation is performed to determine the extent to which each data set falls within the fuzzy set defined for the variables Age, IQ, and Motor Skills. This degree of membership value indicates each data set's membership level within a specific linguistic category (low, medium, high) represented by parameters a through i. This process is the initial step in fuzzy inference because it provides the basis for calculating the rule strength (firing strength) in subsequent stages. Table 3 below presents the complete results of the degree of membership for each data fraction based on the designed triangular membership function.

Table 3. Degree of Membership Results

Data	a	b	c	d	e	f	g	h	i
1	0	0.33	2	0.67	2	0	0	0	1.5
2	0	0.33	2	0	0	1.33	0	1	0
3	1	0	0	0	1	2.67	1	0	0
4	0	0.33	2	0.33	1.75	0	0	1.5	0
5	0	1	0	0	1.25	0	0	0.5	2
6	0	1.67	0	0.5	1	0	1	0	0
7	0.67	2.33	0.67	2	2	0	1	0	0

Firing Strength

The firing strength stage is the process of calculating the strength of each fuzzy rule based on the previously obtained membership degree values. In this stage, the firing strength value is determined from the results of fuzzy logic operations (usually using the minimum or multiplication method) on combinations of input variables according to the conditions of each rule in the rule base. The resulting value reflects the activation level of each rule against the tested data, with a higher value indicating a more relevant rule to the data, as shown in Table 4.

Table 4. Firing Strength Results

Faction	R1(1)	R2(2)	R3(3)	R4(4)	R5(5)
1	2	0	0	0	0
2	0	2.67	0	0	0
3	0	0	1	0	0
4	0	0	0	1	0.875
5	0	0	0	0	0.625
6	0	1.67	0	0	0
7	0	4.67	0	1.56	1.33

Normalization of Firing Strength

The firing strength normalization results should be explained. This step is carried out to adjust the firing strength of each rule to be proportional to the overall total. The firing strength values for each rule in Table 4 are summed to obtain Σα as the divisor. Next, each individual firing strength value is divided by Σα to produce the normalized weight ω_i. This normalization process ensures that the contribution of each rule is proportional, with the total weight of each data point equal to 1. This normalization result forms the basis for calculating the final output of the fuzzy inference system, shown in Table 5.

Table 5. Firing Strength Normalization Results

Σα	w̄1	w̄2	w̄3	w̄4	w̄5
2	1	0	0	0	0
2.67	0	1	0	0	0
1	0	0	1	0	0
1.87	0	0	0	0.53	0.47
0.62	0	0	0	0	1
1.67	0	1	0	0	0
7.56	0	0.61	0	0.20	0.17

Output Final (Weighted Average)

The final stage in the fuzzy inference process is calculating the weighted average to determine the system's crisp output value. At this stage, each normalized weight ω_i obtained from the firing strength normalization process is multiplied by a constant z representing each rule. Then, all multiplication results are summed and divided by the total weights. This method produces a single z value for each data point, reflecting the system's final decision based on the combination of all applicable fuzzy rules. This value is presented in Table 6 as the weighted average result, which forms the basis for determining the predicted class in the next stage.

Table 6. Weighted Average Results

Data	z (weighted average)
1	1
2	2
3	3
4	4.466666667
5	5
6	2

Data	z (weighted average)
7	2.94

Mapping to Classes (Rounding to the Nearest Integer)

The final stage of the classification process is performed by mapping the output values (z) to classes by rounding to the nearest integer. Each weighted average value obtained from the defuzzification stage is mapped to a predetermined class code, as shown in Table 7.

Table 7. Class Mapping

Code	Classes
1	Deafness
2	Blindness
3	Paralysis
4	Mental Retardation
5	Autism

This process ensures that the numerical calculation results can be interpreted into specific categories of special needs. After rounding and mapping, the final prediction results are presented in Table 8, which compares the system's predicted classes with the actual target classes. This stage is crucial for assessing the accuracy of the fuzzy method used to classify special needs based on age, IQ, and motor skills.

Table 8. Final Results

Data	z	Rounded	Class Predictions	Target
1	1	2	Deafness	Deafness
2	2	3	Blindness	Blindness
3	3	4	Paralysis	Paralysis
4	4.67	4	Mental Retardation	Mental Retardation
5	5	5	Autism	Autism
6	2	2	Mental Retardation	Visual Impairment
7	2.94	3	Autism	Paralysis

Triangular fuzzy membership functions for the three input variables used in the classification system: Age, IQ, and Motor Skills.

Top graph (Age Membership Function)

The X-axis shows the age range (0–15 years) and the Y-axis shows the degree of membership (0–1). Age is divided into three fuzzy sets: Low (blue), Medium (green), and High (red). Each triangular curve illustrates how the degree of membership for a given age is calculated. For example, a 5-year-old might have partial membership in the "Low" and "Medium" categories.

Middle graph (IQ Membership Function)

The X-axis shows the range of IQ scores (50–150). It is divided into three categories: Low (blue), Medium (green), and High (red). A given IQ score can have degrees of membership in more than one category simultaneously, depending on its position between the vertices of the triangle.

Bottom graph (Motor Membership Function)

The X-axis shows the range of motor skills scores (0–10). Like the other two variables, motor skills are grouped into Low, Medium, and High.

Taken together, these three graphs illustrate how input numeric values are converted into fuzzy membership degrees. This process allows fuzzy systems to handle uncertain or gradual data, rather than simply hard-and-fast classifications. Each child can be evaluated based on their membership degrees in multiple categories simultaneously. Before inference and defuzzification are performed, as shown in Figure 2.

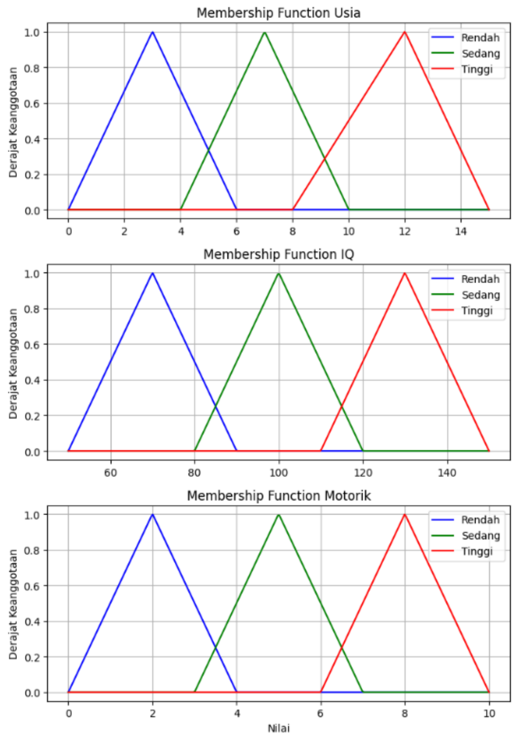

Figure 2. Triangle for Three Input Variables

Based on the test results summarized in Table 8: Final Results, the expert system using the Adaptive Neuro-Fuzzy Inference System (ANFIS) method demonstrated good classification performance in predicting the type of children with special needs (ABK) based on age, IQ, and motor skills.

High Classification Accuracy

Of the 7 test data sets, 6 were successfully predicted according to the target: Data sets 1 through 5 and 6 were predicted correctly. Only the 7th data set was off (predicted Autism while the target was Paralysis). Accuracy level = 6/7 ≈ 85.7%.

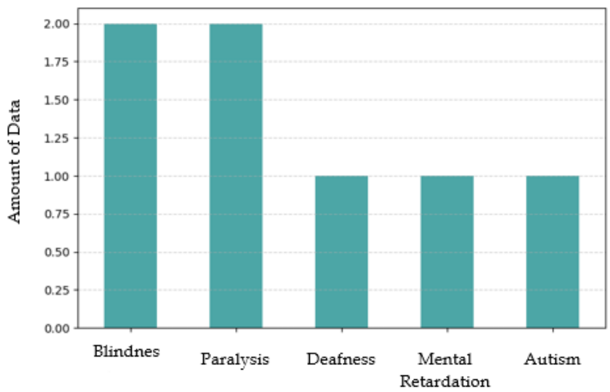

Figure 3. ANFIS Prediction Class Distribution

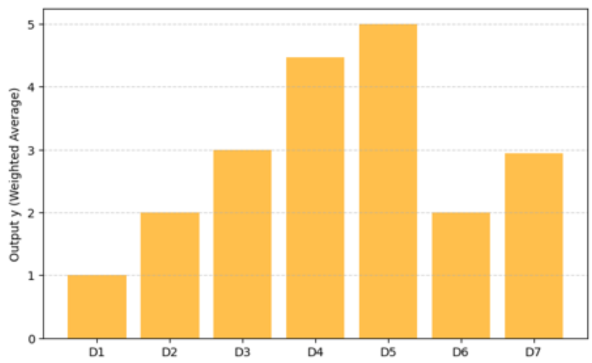

Figure 4. ANFIS output value of each data

Accuracy of the ANFIS Method

The fuzzy process (degree of membership), firing strength calculation, normalization, and weighted average were consistent. The rounded output (rounding to the nearest integer) correctly mapped the z-score to the ABK class.

Source of Mismatch

One prediction error was likely caused by overlapping membership functions or data falling on the boundary between classes, resulting in an ambiguous z-score.

Implications

This model can be used as a tool for teachers and educational staff at Special Needs Schools (SLB) in Southwest Papua to conduct initial identification of the characteristics of children with special needs. With an accuracy of ±86%, this system can expedite the assessment process before further testing.

The ANFIS method approach is effective and reliable for classifying the characteristics of children with special needs, with a high level of accuracy and relatively low error. Improvements can be focused on refining the membership function and adding training data to increase prediction precision.

Conclusion

Based on the results of the research that has been conducted, it shows that the ANFIS model approach is effective in classifying children with special needs in SLB Papua Barat Daya. The system is able to recognize the pattern of relationships between input variables of age, IQ, and motor skills with the results of the classification of the characteristics of special needs children consistently. The test results show quite good model performance, although it is still limited to a relatively small amount of test data. Therefore, the level of accuracy obtained needs to be interpreted carefully and can be improved by expanding the dataset in further research. The main advantage of the ANFIS model approach lies in its ability to combine fuzzy logic to handle uncertainty and artificial neural networks in classification. This allows the system to adjust parameters dynamically, so that the classification results are more stable than conventional approaches. This system can assist teachers in the initial identification of special needs characteristics objectively and efficiently, and can be the basis for the development of digital tools in assessment.

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Author Contributions

Conceptualization, E.E.; methodology, E.E.; software, L.F.; validation, L.F. and E.E.; formal analysis, F.A.; investigation, F.A.; resources, L.F.; data curation, L.F. and F.A; writing—preparation of original draft, E.E and L.F; writing—review and editing, E.E.; visualization, E.E; supervision, X.X.; project administration, X.X.; obtaining funding, Y.Y. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The author declares that there is no conflict of interest in this research. This research was conducted independently and was not influenced by personal interests or professional relationships. All decisions made during the research and writing process were made objectively and with scientific integrity.

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