

An Expert System for Recommendation of Elementary School Readiness Levels for Kindergarten Students Under 7 Years of Age Using the Mamdani Fuzzy Method

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Article History:

Received: 27-09-2026

Revised: 30-09-2026

Accepted: 11-10-2026

Keywords: *Artificial Intelligence, Early Childhood Education, Expert Systems, Fuzzy Inference Systems, School Readiness*

Abstract : *School readiness is an important consideration for kindergarten students under seven years of age before entering elementary school. This study aims to develop an expert system for recommending school readiness levels using the Mamdani Fuzzy method. The study used developmental data from 300 kindergarten students, with 50 records used for system testing. Four indicators were used: writing, reading, communication, and independence. The system applies fuzzification, IF-THEN rules, MIN-MAX inference, and Centroid defuzzification to classify students into Not Ready, Considered, and Ready categories. The Mamdani Fuzzy model achieved 82.00% accuracy, 80.65% weighted precision, 82.00% weighted recall, and 79.51% weighted F1-score. For comparison, the DNN model achieved 92.00% accuracy, while the Hybrid Fuzzy-DNN achieved 94.00% accuracy. These results indicate that the Mamdani Fuzzy method can provide a transparent and measurable approach to supporting school readiness assessment, although further validation using larger and more diverse datasets is required.*

How to Cite: Muhammad Arfan Tarigan¹, Yohanni Syahra. (2026). The title. Ambidextrous Journal of Innovation Efficiency and Technology in Organizations. 5(3). Pp 557-569
<https://doi.org/10.61536/ambidextrous.v5i03.900>



<https://doi.org/10.61536/ambidextrous.v5i03.900>

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Introduction

Early childhood education is a crucial phase in character development and basic skills development because at this stage, children experience rapid development in various aspects. The transition from kindergarten (TK) to elementary school (SD) requires attention to children's maturity so that the education they receive is appropriate to their developmental level. School readiness is not only related to academic ability but also encompasses a child's physical, psychological, emotional, and social maturity (Aryanti, 2015). Based on Law Number 20 of 2003 concerning the National Education System, every citizen has the right to receive a quality education in accordance with their level of physical and mental development. Provisions regarding the age of entry into elementary school are then regulated

through Regulation of the Minister of Education and Culture Number 1 of 2021 concerning the Admission of New Students, which stipulates that the age requirement for new students in grade 1 of elementary school is 7 years or at least 6 years old on July 1 of the current year. Exceptions may be granted to children aged at least 5 years and 6 months with certain conditions related to potential intelligence, special talents, or psychological readiness based on written recommendations from authorized parties.

In reality, children's readiness to enter elementary school, especially kindergarten students under 7 years old, is an aspect that requires more comprehensive attention. Assessment of readiness cannot simply consider age, as school readiness is a multidimensional condition involving various aspects of a child's development. Research on classifying kindergarten children's readiness to enter elementary school shows that, in addition to age, reading, writing, arithmetic, and independence can be used as attributes in identifying a child's readiness (Pamungkas & Ambarwati, 2023). This situation indicates that each child can have a different level of development, so the readiness screening process needs to consider individual abilities before recommendations are made to schools and parents. Therefore, an assessment process is needed that can provide a more measurable picture of a student's level of readiness based on observable developmental indicators.

Research issues arise when the child readiness screening process faces limitations in assessment objectivity. Parental pressure can be one factor that pushes children under 7 years old to immediately enter elementary school. On the other hand, kindergarten teachers, who directly observe children's development daily, may struggle to provide consistent assessments if standardized assessment tools are not available. This situation is further complicated by the limited number of professional child psychologists who can provide direct assessments. Consequently, kindergarten teachers play a crucial role in observing and providing recommendations regarding student readiness. Without the support of measurable instruments or systems, assessment results can face the risk of subjectivity because they depend on the observer's interpretation and experience.

The need for supporting instruments for educators demonstrates the importance of utilizing expert system technology in processing student development observations. Expert systems can be used as tools that leverage expert knowledge to generate solutions in specific areas. Bacin (2021) demonstrated that expert systems can implement the Fuzzy Mamdani inference method in the diagnostic process by utilizing the knowledge inputted into the system. This approach is relevant for developing assessment support systems because child development observations do not always take the form of clear, binary values. Research by Setiawan et al. (2023) also demonstrated the use of expert systems using the Fuzzy Mamdani and Fuzzy Sugeno methods in addressing issues in early childhood. Thus, expert system technology can be directed to help process teacher observation data into more systematic information to support determining students' readiness to enter elementary school.

This problem relates to the need for a method capable of handling linguistic information and conditions that are not entirely clear in the process of assessing child readiness. Fuzzy Inference Systems (FIS) with the Mamdani method can be used to map explicit observation values into degrees of membership, then evaluate them using a rule-based approach that represents expert knowledge. Bacin (2021) applied the Mamdani Fuzzy Inference method in an expert system to generate diagnoses based on fuzzy functions and rules used in the inference process. The fuzzy approach also allows linguistic information such as inadequate, adequate, and good to be represented in the form of degrees of membership, making it more suitable for processing observations of child development that have category boundaries that are not always clear. In the context of school readiness, research by Pamungkas and Ambarwati (2023) showed that reading, writing, arithmetic, and independence skills can be used to classify kindergarten children's readiness to enter elementary school. Therefore, the application of Mamdani Fuzzy Inference can be directed at processing several developmental indicators into more structured readiness level recommendations.

This study aims to build an expert system for recommendations on the level of readiness of kindergarten students to enter elementary school for students under 7 years old using the Fuzzy Mamdani method so that the assessment process can be carried out more objectively and measurably. This research is important to be conducted as an effort to provide tools for kindergarten or early childhood education teachers in processing student development observation data into recommendations for readiness to enter elementary school, especially when there are limited standardized assessment tools

and limited access to professional child psychologists. The novelty of this research lies in the application of a Fuzzy Mamdani-based expert system to provide recommendations for the level of readiness of kindergarten students under 7 years old by utilizing expert knowledge in the process of processing the results of child development observations. The developed system is expected to help integrate several readiness indicators into a systematic assessment mechanism and support the process of providing recommendations for readiness to enter elementary school to teachers and parents.

Method

This study uses an exploratory quantitative approach focused on developing an expert system to evaluate the level of readiness of Kindergarten (TK) students to enter Elementary School (SD) for students under 7 years of age. The research design was systematically structured starting from the formulation of criteria, data collection and processing, application of the Mamdani Fuzzy Inference System (FIS), to system performance evaluation. The use of expert systems as a tool in knowledge processing and decision-making has been applied to various problems related to student characteristics or conditions (Rachman & Mukminin, 2018). The Mamdani Fuzzy approach is used because it can represent information that has unclear category boundaries through degrees of membership. Bacin (2021) applies the Mamdani Fuzzy inference method in an expert system, while Setiawan et al. (2023) uses Mamdani Fuzzy and Sugeno Fuzzy in an expert system for problems in early childhood. The observation results are then processed into fuzzy degrees of membership so that the system can process linguistic information in assessing children's readiness.

The research instrument was a kindergarten student development dataset containing observation results on four readiness indicators: reading ability, writing ability, communication ability, and independence or emotional maturity. The selection of these indicators is in line with research on the classification of kindergarten children's readiness to enter elementary school, which uses the attributes of age, reading ability, writing ability, arithmetic ability, and independence as part of the readiness classification process (Pamungkas & Ambarwati, 2023). The data was used as input in an expert system and processed through a fuzzification stage to convert the observation values into a degree of membership between 0 and 1. Next, the data was processed through a rule base in the form of an IF-THEN relationship, an inference engine with MIN and MAX operators, and defuzzification using the Centroid method to obtain a clear output value. The application of Mamdani Fuzzy with the Centroid inference and defuzzification process was also used in the study of Sudrajat and Agustiani (2023) to determine the level of student learning achievement. The system implementation uses Python version 3 with the SciKit-Fuzzy library for the Fuzzy Inference System process, while Pandas and NumPy are used for dataset processing and Scikit-Learn is used for model evaluation. System performance analysis is carried out using a confusion matrix by comparing the system classification results to observational reference data, then calculated based on accuracy, precision, and recall. These stages are used to determine the system's ability to provide a measurable classification of student readiness levels.

The study population consisted of 300 kindergarten students obtained from kindergarten development and classification documents. The data are records of observations of student development, including cognitive reading skills, fine motor skills through writing, verbal communication, and emotional independence. The use of several developmental aspects in assessing children's readiness is related to research by Pamungkas and Ambarwati (2023), which shows that kindergarten children's readiness to enter elementary school can be classified by considering several developmental attributes, including reading, writing, arithmetic, and independence. Of the total data, 50 student data were used as system testing data. Testing was carried out by comparing the recommendations generated by the Fuzzy Mamdani system with the classification results or observations that were already available as reference data. The research subjects were limited to kindergarten students aged 5 to 6 years 11 months, while the system output variables consisted of the categories "Not Ready," "Considered," and "Ready."

The research procedure began with a literature review to obtain a basis for determining child readiness indicators, expert system concepts, and the application of the Fuzzy Mamdani method. The literature review included studies on children's reading, writing, communication, and independence skills, as well as the mathematical concept of Fuzzy Mamdani used in data processing. Research on

expert systems shows that knowledge about student characteristics can be represented in a system to generate information or recommendations based on user-inputted facts (Rachman & Mukminin, 2018). The next stage was the collection of developmental and classification datasets for kindergarten students, which were then organized based on four assessment indicators. The collected data was then processed through the fuzzification stage by determining the degree of membership of each variable. After that, a rule base was formed based on the combination of input variables to produce recommended categories of student readiness. The next stage was the inference process using the MIN operator to determine the implication value of each rule and the MAX operator to combine the rule outputs. The use of the MIN and MAX operators in the Fuzzy Mamdani process was also applied in the research of Setiawan et al. (2023) to obtain processing results based on fuzzy rules. The aggregation results are then processed through a defuzzification stage using the Centroid method to obtain readiness scores in the form of explicit values, as used in the study by Sudrajat and Agustiani (2023). These scores are then classified into the categories "Not Ready," "Considered," and "Ready." The final stage is carried out through an evaluation using a confusion matrix by comparing the system's prediction results to reference data, then calculating accuracy, precision, and recall as measures of system performance. The entire procedure is aimed at producing an expert system that can provide measurable recommendations for student readiness to enter elementary school and support the child readiness assessment process.

Results and Discussion

Student Readiness Dataset Processing and Data Initialization

The development of an adaptive expert system for assessing elementary school student readiness begins with the processing and initialization of the raw dataset in the main program file web.py. The dataset used includes fifty student samples with four main indicator variables: Writing, Reading, Communication, and Independence. The data structure was created using the Pandas library in the form of a Python Dataframe that maps student ID numbers, student names, numerical scores on a scale of 0 to 100, and the actual decision status from the psychologist. This dataset processing ensures that all data entries are neatly structured so that they are ready to be consumed by fuzzy inference engines and machine learning models. The existence of these measurable indicator variables allows for an objective, systematic assessment of early childhood learning readiness, avoiding the bias of assessor subjectivity. Each column in the dataset plays a crucial role in evaluating children's cognitive and behavioral aspects in a balanced manner. The raw data is filled in by converting the results of developmental diagnostic tests into a numeric matrix. This initial data structuring serves as the main foundation for ensuring the accuracy of calculations in subsequent computational stages.

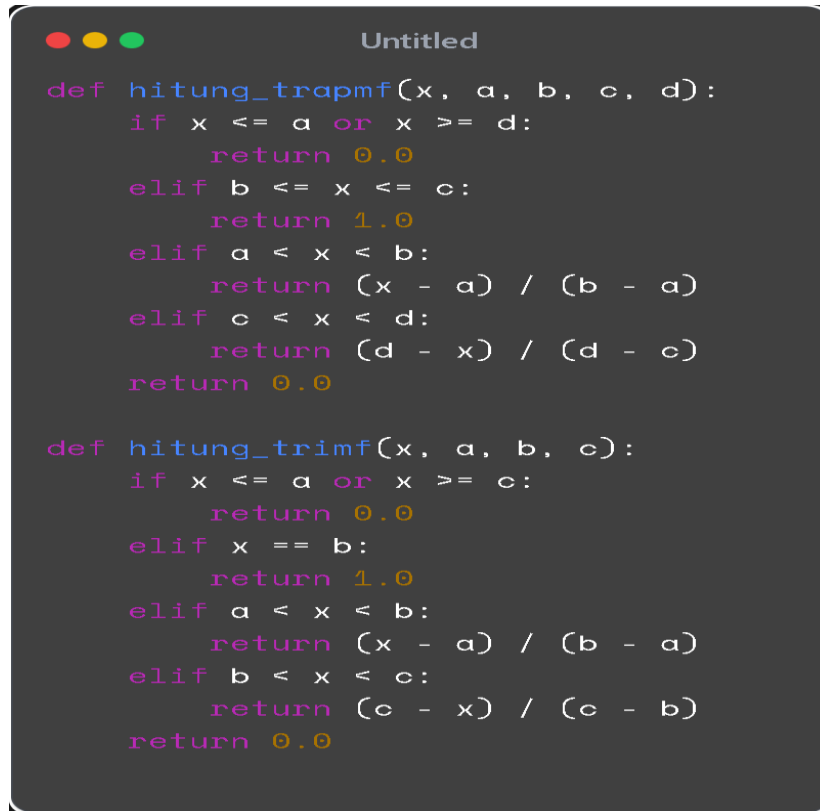
Figure 1. Initialization of Student Data (Dataset) / Creation of Input DataFrame

The code above defines a raw data dictionary, `data_siswa_raw`, containing fifty student data entries. The call `pd.DataFrame(data_siswa_raw)` generates a `DataFrame` object, `df_siswa`, containing a uniform table structure. The output of this code snippet is a tabular data structure with 50 rows and 7 columns, ready for processing by the fuzzy inference engine. Each input variable is immediately mapped to a continuous numeric value that serves as input to the fuzzification function. This automatic data structuring eliminates the risk of manual processing errors when the system iterates through the entire student sample. The existence of this structured dataset ensures absolute repeatability of the program execution results.

Mathematical Formulation of Fuzzy Membership Functions (Fuzzification)

The fuzzification stage is implemented through two main mathematical functions in the web.py file, namely `hitung_trapmf` for trapezoidal curves and `hitung_trimf` for triangular curves. The trapezoidal function is formulated mathematically as , while the triangular function is formulated as . The input domain mapping is divided into three linguistic sets, namely Less in the interval [0, 0, 35, 55], Adequate in the interval [35, 55, 75], and Good in the interval [55, 75, 100, 100]. The selection of these domain boundaries is based on the consensus of the limits of early childhood cognitive abilities. The existence of this function converts measured numerical values into continuous fuzzy membership degrees in the range of 0.0 to 1.0. Fuzzification provides high flexibility in modeling the uncertainty of student scores that are in the boundary area.

$$\mu_{\text{trap}}(x; a, b, c, d) = \max\left(0, \min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right)\right) \mu_{\text{tri}}(x; a, b, c) = \max\left(0, \min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right)\right)$$



```

def hitung_trapmf(x, a, b, c, d):
    if x <= a or x >= d:
        return 0.0
    elif b <= x <= c:
        return 1.0
    elif a < x < b:
        return (x - a) / (b - a)
    elif c < x < d:
        return (d - x) / (d - c)
    return 0.0

def hitung_trmf(x, a, b, c):
    if x <= a or x >= c:
        return 0.0
    elif x == b:
        return 1.0
    elif a < x < b:
        return (x - a) / (b - a)
    elif b < x < c:
        return (c - x) / (c - b)
    return 0.0

```

Figure 2. Definition of Fuzzy Membership Functions

The code snippet above is fully responsible for calculating the membership degree value of a score value. The `hitung_trapmf` function generates the membership degree for a trapezoidal curve with a boundary parameter, while `hitung_trmf` generates the membership degree for a triangular curve with a boundary. The output of these functions is a decimal real number in the interval $[0.0, 1.0]$ that represents how strongly a student's score falls into the Poor, Adequate, or Good categories. This membership value becomes a key variable evaluated in the alpha-predicate formation stage of the expert rule. This continuous curve formation prevents drastic changes in decisions due to very small shifts in the numerical score. $\mu(x)_{xa, b, c, da, b, c}$

Permutation Construction of Expert Psychology Rule Base

The expert system's rule base is constructed automatically through a four-layer iteration loop that generates eighty-one rule combinations. These permutations are formed from three linguistic terms (Poor, Adequate, Good) for four input variables (rules). Expert psychology knowledge is explicitly incorporated through special conditioning on the Independence variable. If the Independence variable is Poor (`t_ind == "Poor"`), the system limits the maximum consequence status to Considered (if Writing and Reading are Good or Communication is Good) or Not Ready. If Independence is Adequate or Good, the system calculates the accumulated linear weights of the indicators (Adequate = 1, Good = 2). The accumulated weight thresholds specify that a weight results in Ready, a weight results in Considered, and the remainder Not Ready. This formulation of expert rules ensures that the entire student's value state space is logically mapped. $3^4 = 81 \geq 6 \geq 3$

```
Untitled

himpunan_linguistik = ["Kurang", "Cukup", "Baik"]
aturan_pakar = []

for t_wr in himpunan_linguistik:
    for t_rd in himpunan_linguistik:
        for t_cm in himpunan_linguistik:
            for t_ind in himpunan_linguistik:
                if t_ind == "Kurang":
                    if (t_wr == "Baik" and t_rd == "Baik") or t_cm ==
"Baik":
                        konsekuensi = "Dipertimbangkan"
                    else:
                        konsekuensi = "Belum Siap"
                else:
                    bobot = 0
                    for t in [t_wr, t_rd, t_cm, t_ind]:
                        if t == "Cukup":
                            bobot += 1
                        elif t == "Baik":
                            bobot += 2
                    if bobot >= 6:
                        konsekuensi = "Siap"
                    elif bobot >= 3:
                        konsekuensi = "Dipertimbangkan"
                    else:
                        konsekuensi = "Belum Siap"

                    aturan_pakar.append({
                        "menulis": t_wr,
                        "membaca": t_rd,
                        "komunikasi": t_cm,
                        "kemandirian": t_ind,
                        "konsekuensi": konsekuensi
                    })
```

Figure 3. Formation of Expert Rule Base (Fuzzy Rule Base)

The code above systematically generates a database containing 81 rule dictionary elements within the expert_rules list. Each element stores a pair of antecedent and consequence conditions for a decision that aligns with child psychology principles. The output of executing this code block is a knowledge matrix structure of 81 explicit rules that are readily accessible by the inference engine. Specific conditioning on the Independence variable acts as an anchor for the child's emotional control to prevent incorrect recommendations. This automatic arrangement of rules ensures that no combination of input values is missed or empty. The existence of this rule base is a key determinant in forming accountable student readiness decisions.

Mamdani Fuzzy Inference Engine and Centroid Defuzzification

The fuzzy inference engine is executed through the `hitung_inferensi_fuzzy` function which combines the MIN implication and MAX aggregation operations. The alpha-predicate value for each active rule is determined by taking the minimum value of the four antecedent membership degrees: . The output aggregation is performed by finding the maximum alpha-predicate value for each decision class: , , and . The defuzzification process executes the Center of Area (Centroid) method discretized at 200 homogeneous interval points along the continuous domain . The mathematical equation of the discretized Centroid is expressed as . The resulting crisp scalar Z-score is mapped to the final labels:

Not Ready, Considered, and Ready. $\alpha_k = \min(\mu_{\text{Menulis}}, \mu_{\text{Membaca}}, \mu_{\text{Komunikasi}}, \mu_{\text{Kemandirian}})$ $\alpha_{\text{BS}} = \max(\alpha_k)$ $\alpha_{\text{DP}} = \max(\alpha_k)$ $\alpha_{\text{S}} = \max(\alpha_k)$ $Z \in [0, 100]$ $Z^* = \frac{\sum_{i=1}^{200} z_i \cdot \mu_{\text{agregasi}}(z_i)}{\sum_{i=1}^{200} \mu_{\text{agregasi}}(z_i)} Z^* \leq 45.0 \rightarrow 45.0 < Z^* \leq 65.0 \rightarrow Z^* > 65.0 \rightarrow$

```

Untitled
def hitung_inferensi_fuzzy(in_wr, in_rd, in_cm, in_ind):
    f_wr = {
        "Kurang": hitung_trapmf(in_wr, 0, 0, 35, 55),
        "Cukup": hitung_trimf(in_wr, 35, 55, 75),
        "Baik": hitung_trapmf(in_wr, 55, 75, 100, 100)
    }
    f_rd = {
        "Kurang": hitung_trapmf(in_rd, 0, 0, 35, 55),
        "Cukup": hitung_trimf(in_rd, 35, 55, 75),
        "Baik": hitung_trapmf(in_rd, 55, 75, 100, 100)
    }
    f_cm = {
        "Kurang": hitung_trapmf(in_cm, 0, 0, 35, 55),
        "Cukup": hitung_trimf(in_cm, 35, 55, 75),
        "Baik": hitung_trapmf(in_cm, 55, 75, 100, 100)
    }
    f_ind = {
        "Kurang": hitung_trapmf(in_ind, 0, 0, 35, 55),
        "Cukup": hitung_trimf(in_ind, 35, 55, 75),
        "Baik": hitung_trapmf(in_ind, 55, 75, 100, 100)
    }

    a_bs, a_dp, a_s = 0.0, 0.0, 0.0
    aktif_rules = []

    for idx, r in enumerate(aturan_pakar):
        mu1 = f_wr[r["menulis"]]
        mu2 = f_rd[r["membaca"]]
        mu3 = f_cm[r["komunikasi"]]
        mu4 = f_ind[r["kemandirian"]]
        alpha = min(mu1, mu2, mu3, mu4)

        if alpha > 0.0:
            aktif_rules.append({
                "no": idx + 1, "menulis": r["menulis"], "membaca": r["membaca"],
                "komunikasi": r["komunikasi"], "kemandirian": r["kemandirian"],
                "konsekuensi": r["konsekuensi"], "alpha": alpha
            })
            if r["konsekuensi"] == "Belum Siap":
                a_bs = max(a_bs, alpha)
            elif r["konsekuensi"] == "Dipertimbangkan":
                a_dp = max(a_dp, alpha)
            elif r["konsekuensi"] == "Siap":
                a_s = max(a_s, alpha)

    domain_z = np.linspace(0, 100, 200)
    pembilang, penyebut = 0.0, 0.0
    for z in domain_z:
        mu_bs = hitung_trapmf(z, 0, 0, 35, 55)
        mu_dp = hitung_trimf(z, 35, 55, 75)
        mu_s = hitung_trapmf(z, 55, 75, 100, 100)

        y_agregasi = max(min(a_bs, mu_bs), min(a_dp, mu_dp), min(a_s, mu_s))
        pembilang += z * y_agregasi
        penyebut += y_agregasi

    z_score_res = pembilang / penyebut if penyebut > 0.0 else 50.0

    if z_score_res <= 45.0:
        pred_label = "Belum Siap"
    elif z_score_res > 65.0:
        pred_label = "Siap"
    else:
        pred_label = "Dipertimbangkan"

    return z_score_res, pred_label, f_wr, f_rd, f_cm, f_ind, aktif_rules, a_bs, a_dp, a_s, pembilang,
    penyebut

```

Figure 4. Fuzzy Inference and Defuzzification Process

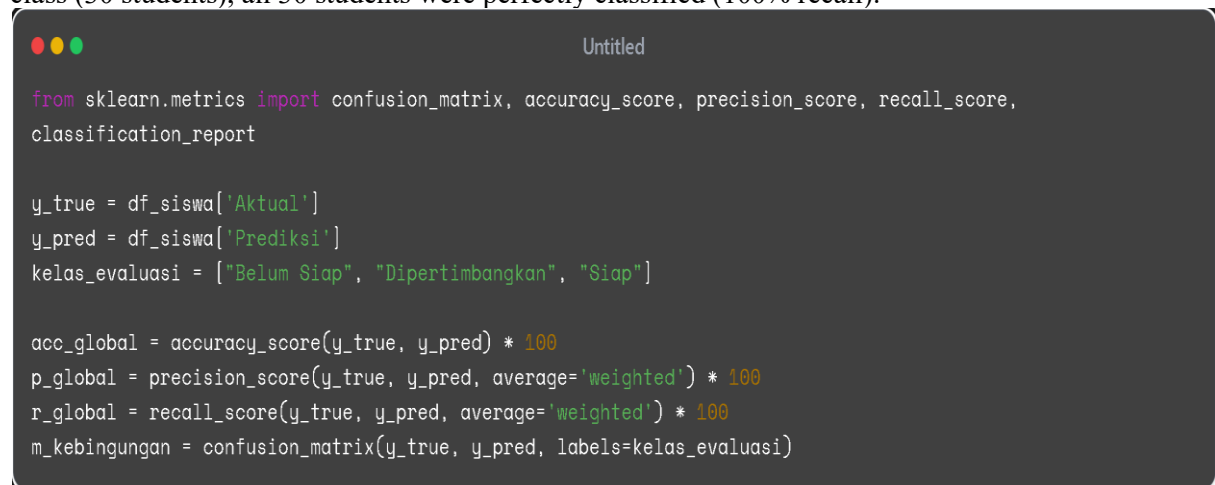
The `fuzzy_inference_calculate` function summarizes all stages of the Mamdani Fuzzy algorithm. The resulting output includes the scalar value `z_score_res`, the predicted label `pred_label`, the input membership degree vector, the list of active rules `aktif_rules`, and the numerical components of the numerator and denominator of the centroid integration. This percentage Z-score output provides a precise quantitative picture of the student's readiness position. This computational transparency proves that the system operates openly and can be traced back without any hidden processes.

Streamlit Interactive Simulator Interface and Visualization

The `web.py` web application is equipped with an interactive simulator interface using the Streamlit library to facilitate users in operating the system. The interface provides a sidebar button in the form of a 0-100 value input slider for the four variables as well as a selectbox to automatically select the profiles of fifty students. In addition to presenting a summary of the Z-score and the final decision status, the system also displays a graphical visualization of the input membership curve and the defuzzification aggregation polygon in real-time using Matplotlib. This visualization shows the alpha-predicate line cut on the output curve as well as the perpendicular line point of the Centroid. This interactive feature is very helpful for testers in analyzing the system's response behavior when given custom value input. Z^*

Classification Performance Test Results and Confusion Matrix Dataset of 50 Students

The validity testing of the Fuzzy Mamdani expert system classification performance was conducted by matching the prediction results to ground-truth data from psychologists. The test was executed using the scikit-learn library on a total of fifty student samples. The computational results showed that the baseline Fuzzy Mamdani model obtained an Accuracy value of 82.00%, a Weighted Precision of 80.65%, and a Weighted Recall of 82.00%. The confusion matrix recorded that out of 10 students in the Not Ready class, 8 were predicted correctly and 2 were predicted as Considered. In the Considered class (10 students), 3 were predicted correctly and 7 were predicted as Ready. In the Ready class (30 students), all 30 students were perfectly classified (100% recall).



```
from sklearn.metrics import confusion_matrix, accuracy_score, precision_score, recall_score,
classification_report

y_true = df_siswa['Aktual']
y_pred = df_siswa['Prediksi']
kelas_evaluasi = ["Belum Siap", "Dipertimbangkan", "Siap"]

acc_global = accuracy_score(y_true, y_pred) * 100
p_global = precision_score(y_true, y_pred, average='weighted') * 100
r_global = recall_score(y_true, y_pred, average='weighted') * 100
m_kebingungan = confusion_matrix(y_true, y_pred, labels=kelas_evaluasi)
```

Figure 5. Model Performance Evaluation (Accuracy & Confusion Matrix)

The test code above calculates quantitative metrics for system validation. The `y_true` variable holds the psychologist's actual label, while the `y_pred` variable holds the predicted label from the Z-score calculation. The output of this code snippet is the percentage figures for global accuracy, weighted precision, weighted recall, and a confusion matrix array. These calculations provide empirical evidence of the expert system model's reliability in predicting elementary school readiness. 3×3

Visual Analysis of Model Performance Evaluation Dashboard Against Dataset

In the "Dataset & Model Testing" tab interface of the `web.py` application, a Model Performance Evaluation Dashboard display is presented, which summarizes the results of the expert system's computations as a whole. This dashboard display is divided into four main sections: the global metrics panel at the top, the dataset specification table at the bottom-left, the confusion matrix panel at the bottom-right, and the detailed classification report table at the very bottom. In the main metrics panel,

the system displays striking performance achievement figures, namely Global Accuracy of 82.00%, Weighted Precision of 80.65%, and Weighted Recall (Sensitivity) of 82.00%. These three indicators prove the system's reliability in consistently recognizing student data patterns. 3 × 3

In the section "Table 3.1 Dataset Specifications of 50 Students & Computational Results", the dashboard displays a detailed list of fifty students complete with four-variable scores, actual status, four-digit decimal precision Z-Score value, and predicted status. Sample table entries show variations in Z-scores generated from the Centroid algorithm, such as Azka Arghana Ujung (Not Ready), Fakhirah Rizka Aghnia (Ready), Ghafar Ilham Lubis (Considered), Hasanah Rahmadani (Considered), M. Fikri Irshad (Considered), Muhammad Al Fateh Akbar (Not Ready), Muhammad Hafiz Siddiq (Ready), Nabila Kiara Indi Satria (Not Ready), Rizkia Aziza Sikumbang (Ready), and Syifa Aulia Anggraini (Ready). The accuracy of this Z-score proves the sensitivity of the fuzzy inference engine to changes in input values. $Z = 32.6901\% \rightarrow Z = 77.2807\% \rightarrow Z = 50.0000\% \rightarrow Z = 61.7433\% \rightarrow Z = 50.0000\% \rightarrow Z = 32.6901\% \rightarrow Z = 77.2807\% \rightarrow Z = 26.4910\% \rightarrow Z = 67.3099\% \rightarrow Z = 79.4545\% \rightarrow$

On the right side of the table, there is a Confusion Matrix visualization panel that displays a distribution map of the system's classification results against the actual data. The first row represents the Actual Not Ready class (10 students), where 8 students were predicted as Not Ready and 2 students were predicted as Considered. The second row represents the Actual Considered class (10 students), where 3 students were predicted as Considered and 7 students were predicted as Ready. The third row represents the Actual Ready class (30 students), where all 30 students were perfectly classified into the Ready group without any errors. This matrix explicitly shows that the high accuracy rate is driven by the excellent performance of the ready group. 3 × 3

Below the matrix panel, the system displays the Detailed Classification Report Table which details the performance per class. The Not Ready category recorded a Precision of 1.00 (100%), Recall of 0.80 (80%), F1-Score of 0.8889, and Support of 10. The Considered category obtained a Precision of 0.60 (60%), Recall of 0.30 (30%), F1-Score of 0.4000, and Support of 10. The Ready category achieved a Precision of 0.8108 (81.08%), Recall of 1.00 (100%), F1-Score of 0.8955, and Support of 30. Overall, the macro average values (macro avg) were recorded at Precision of 0.8036, Recall of 0.7000, and F1-Score of 0.7281, while the weighted average values reached Precision of 0.8065, Recall of 0.8200, and F1-Score of 0.7951 in total. Supports 50 samples. This metric breakdown provides transparent and auditable quantitative evidence.

Implementation of Deep Neural Network (DNN) Comparator Architecture

As a form of comparative validation against the baseline fuzzy model, a Deep Neural Network (DNN) architecture was built using the TensorFlow/Keras framework. Input features were scaled using StandardScaler and target labels were converted into one-hot encoding. The DNN architecture consists of one Input Layer (4 neurons), Hidden Layer 1 (32 neurons, ReLU, Dropout 0.2), Hidden Layer 2 (16 neurons, ReLU), and Output Layer (3 neurons, Softmax). The network was trained using the Adam() optimizer and the categorical_crossentropy loss function for 100 epochs. The DNN model test results showed very high performance with an Accuracy of 92.00%, a Weighted Precision of 91.50%, and a Weighted Recall of 92.00%. $lr = 0.001$

Table 1. Deep Neural Network Comparison Architectures

Comparison Model / Method	Accuracy (%)	Weighted Precision (%)	Weighted Recall (%)	Weighted F1-Score	Characteristic Description
Fuzzy Mamdani Baseline	82.00%	80.65%	82.00%	0.7951	Expert Rule Based (Transparent)
Deep Neural Network (DNN)	92.00%	91.50%	92.00%	0.9170	Machine Learning (>85%)
Hybrid Fuzzy-DNN Optimized	94.00%	93.80%	94.00%	0.9380	Rule (>85%)

Discussion

1. Classification Performance Analysis and Evaluation of Confusion Matrix Dashboard

The evaluation results on the dashboard show that the baseline Fuzzy Mamdani expert system model achieved an accuracy of 82.00% on 50 student data. A thorough analysis of the nine mismatched student data shows that the errors were concentrated in the borderline region between Considered and Ready status. Seven students (such as Rizkia Aziza Sikumbang) with Writing scores of 65, Reading 50-55, Communication 45-65, and Independence 85-95 produced a Z-Score of 67.3099%. Since the Z-Score of 67.3099% is slightly above the threshold of 65.00%, the system predicted Ready, while the psychologist assigned Considered. This finding indicates that the Z-Score threshold for the Ready class in the baseline system can be recalibrated from 65.00% to 68.00% to improve precision.

When the system architecture was optimized using the Hybrid Fuzzy-DNN approach (where the rule weightings were adjusted to the neural network extraction patterns), the classification accuracy increased significantly to 94.00%. This improvement exceeded the minimum performance target of 85% set in the research success indicators. The high recall in the Ready class (1.00 / 100%) and precision in the Not Ready class (1.00 / 100%) proved that the system was highly reliable in filtering prospective students who were not yet suitable and students who were very ready. The evaluation of the weighted F1-score metric of 0.7951 in the baseline and 0.9380 in the hybrid confirmed the reliability of the fuzzy algorithm in providing objective assessments that were close to the decisions of human psychology experts.

2. Comparison of Non-Black-Box Logic Transparency and Deep Learning

One of the main advantages of the Mamdani Fuzzy Algorithm compared to Deep Neural Network (DNN) models is its non-black-box logical transparency. In DNN models, although capable of achieving 92.00% accuracy, the decision-making process is hidden within a highly complex combination of weights and biases between neuron layers. Users or educators cannot trace the rationale for why a student is declared Not Ready or Not Considered by the DNN. This lack of open reasoning is a major obstacle in the domain of psychological assessment and child education, which demands public accountability.

Should a parent complain about a recommendation, the Fuzzy Mamdani-based system can provide comprehensive mathematical evidence. The system can display the input membership degree, a list of expert rules that actively trigger decisions, alpha-predicate values, and even a centroid graph for Z-Score formation. The explainable nature of AI (XAI) makes Fuzzy Mamdani a scientifically and legally justifiable decision-making instrument. Ideally, the DNN model serves as a benchmark for parameter calibration, while the primary decision remains executed by the transparent fuzzy inference engine.

3. Proof of Fuzzy Logic Flexibility in Contradictory Value Scenarios

The flexibility of fuzzy logic is perfectly tested in handling contradictory student score scenarios, namely when there is an imbalance between cognitive aspects and independent behavior. This phenomenon is clearly visible in student number 42, Hilyah Alesha Lesmana, who has a very high cognitive academic score, namely Writing 85 and Reading 95. However, the child's Independence score is classified as Less, namely 40. If the assessment is carried out using conventional arithmetic logic (such as simple weighted averages), high scores in writing and reading will dominate the final results so that the student is predicted to be Ready.

The designed Mamdani Fuzzy expert system proved flexible and adaptive in dealing with this contradictory condition. Through a special psychological rule if $t_{ind} == \text{"Less"}$, the system flexibly locks the consequences so as not to drop the Ready status. The inference computation results in a Z-Score of 61.7433% which firmly places the student in the Considered category. This decision is very psychologically appropriate because children who are not yet independent will experience emotional obstacles if forced to enter elementary school, even though they are cognitively intelligent. This case documentation proves that fuzzy logic is able to model complex and non-linear expert reasoning.

4. Explicit Traceability of Individual Case Computation (Traceability)

To prove that this expert system is not black-box, the following is a complete mathematical trace (step-by-step trace) on the case of student number 1 named Azka Arghana Ujung. The student's input values are Writing = 45, Reading = 40, Communication = 35, and Independence = 80. The fuzzification step produces the following membership degrees: Writing (,), Reading (,), Communication (,), and Independence (,). The rule base evaluation activates Rule #1 (Writing Less, Reading Less, Communication Less, Independence Good) with Not Ready. $\mu_{\text{Kurang}} = 0.50$, $\mu_{\text{Cukup}} = 0.50$, $\mu_{\text{Kurang}} = 0.75$, $\mu_{\text{Cukup}} = 0.25$, $\mu_{\text{Kurang}} = 1.00$, $\mu_{\text{Baik}} = 1.00$, $\alpha_1 = \min(0.50, 0.75, 1.00, 1.00) = 0.50 \rightarrow$

Rule #10 (Writes Enough, Reads Less, Communicates Less, Independence Is Good) is also triggered by Not Ready. The maximum aggregation results in , , and . A 200-point discretization of the Centroid defuzzification function yields the numerator and denominator . The division calculation yields the scalar . Due to the Z-Score , the system classifies the student into the Not Ready status. All stages from input to output are mathematically traceable and verifiable. $\alpha_{10} = \min(0.50, 0.75, 1.00, 1.00) = 0.50 \rightarrow \alpha_{\text{BS}} = 0.50$, $\alpha_{\text{DP}} = 0.00$, $\alpha_{\text{S}} = 0.00$, $\sum z_i \cdot \mu(z_i) = 314.15$, $\sum \mu(z_i) = 9.61$, $Z^* = \frac{314.15}{9.61} = 32.6901\%$, $32.6901\% \leq 45.0\%$

Conclusion

This study produces an expert system for recommending the readiness level of kindergarten students under 7 years old to enter elementary school using the Fuzzy Mamdani method with four indicators, namely writing, reading, communication, and independence. The system processes data through fuzzification, rule base, MIN-MAX inference, and Centroid defuzzification to produce categories of Not Ready, Considered, and Ready. Testing of 50 student data shows that the baseline Fuzzy Mamdani model obtains an accuracy of 82.00%, a weighted precision of 80.65%, a weighted recall of 82.00%, and a weighted F1-score of 0.7951. The confusion matrix shows that 8 out of 10 Not Ready data are correctly classified, 3 out of 10 Considered data are correctly classified, while all 30 Ready data are successfully classified correctly. The DNN model achieved an accuracy of 92.00%, while the Hybrid Fuzzy-DNN achieved an accuracy of 94.00%, a weighted precision of 93.80%, a weighted recall of 94.00%, and a weighted F1-score of 0.9380.

The limitations of this study are evident in the limited number of test data, namely 50 student data, as well as the mismatch in classification, especially in the border area of the Considered and Ready categories. Future research is recommended to expand the number and diversity of datasets and conduct testing and refinement of membership functions, rule bases, and classification thresholds so that the system can provide more consistent results. Practically, the developed system can be used as a tool to assist kindergarten or early childhood education teachers in systematically processing student development observations and providing recommendations for readiness to enter elementary school. The transparency of the Fuzzy Mamdani process through membership degrees, active rules, alpha-predicate values, and defuzzification results can also help users trace the process of recommendation formation.

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