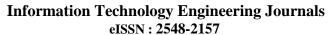
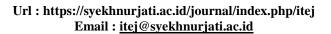
ITE.I







Development of an Expert System for Identifying Students' Learning Styles Using the Euclidean Probability Method

Putri Rahma Informatics Engineering Malikussaleh University Lhokseumawe, Indonesia putri.210170017@mhs.unimal.ac.id Zahratul Fitri Informatics Engineering Malikussaleh University Lhokseumawe, Indonesia zahratulfitri@unimal.ac.id Wahyu Fuadi Informatics Engineering Malikussaleh University Lhokseumawe, Indonesia wahyu.fuadi@unimal.ac.id

Abstract—Learning styles play an important role in determining effective teaching strategies by aligning instructional methods with students' individual preferences in receiving, processing, and understanding information. However, classroom teaching often applies uniform methods without considering these differences, which can reduce learning effectiveness. This study aims to develop a web-based expert system using the Euclidean Probability method to identify the dominant learning styles of students at SMK Negeri 3 Lhokseumawe. The system processes input data representing student characteristics and calculates their proximity to each learning style category. Analysis of 110 student data entries revealed that 32 students (29.09%) had a Visual learning style, 26 students (23.64%) were Auditory, 16 students (14.55%) were Read/Write, and 36 students (32.73%) were Kinesthetic. The results showed that the Kinesthetic learning style was the most dominant among students. Expert validation demonstrated an accuracy rate of 92%, proving the system's reliability in accurately classifying learning styles. This system is expected to serve as a tool in developing more personalized and adaptive learning strategies to enhance student engagement and learning outcomes.

Keywords—Learning Styles, Expert System, Euclidean Probability, Adaptive Learning

I. Introduction

Learning styles refer to an individual's tendencies in absorbing, understanding, and processing information during the learning process, serving as an important guideline in determining appropriate learning approaches [1], [2]. Each student has a different learning style preference. Some students feel more comfortable when the material is delivered visually, such as through images or writing on the board. Others comprehend the material more easily through verbal explanations, while some show higher learning effectiveness through interactive group discussions. This fact indicates that each individual has a unique learning tendency. Therefore, the implementation of learning strategies tailored to students' learning styles has been proven to significantly enhance the effectiveness of the learning process and contribute positively to the improvement of academic achievement [3].

The VARK model (Visual, Auditory, Read/Write, Kinesthetic), developed by Fleming, has been widely used as an instrument to identify individual learning modalities.

This model has proven effective in explaining the differences in students' learning preferences [4].

However, in practice, classroom teaching methods are often uniform for all students. This causes students whose learning styles do not align with the teacher's teaching style to be less optimal in receiving the material, ultimately leading to boredom in the learning process [5]. One solution to address this issue is the use of expert systems. An expert system is a computer-based application designed to mimic an expert's decision-making ability in solving specific problems[6], [7]. Through expert systems, teachers can be assisted in accurately and efficiently identifying students' learning styles.

One method that can be applied in expert systems is the Euclidean Probability method. This method is used to calculate the likelihood of an event occurring by considering various relevant factors. Each factor contributing to the event is measured using the Euclidean distance formula, where the smaller the resulting distance value, the higher the probability that the event belongs to a specific category [8].

Several studies have implemented the Euclidean Probability method in expert systems across various domains. One study developed an expert system with Euclidean Probability method to diagnose diseases in koi fish, achieving an accuracy rate of 95.91% [9]. Another study applied the Euclidean Probability method to identify diseases in cassava plants, demonstrating its effectiveness in agricultural diagnostics [10] The Euclidean Probability method was also used to diagnose dermatic bacterial infections, resulting in an accuracy of 86% [11] Additionally, Euclidean Probability method was implemented to diagnose plant-disturbing organisms in rice plants, achieving 90% accuracy based on validated data [12]. These studies indicate that the Euclidean Probability method enhances the accuracy and reliability of expert systems in various fields. However, its application in the field of education particularly in identifying students' learning styles remains very limited.

This research was conducted at SMK Negeri 3 Lhokseumawe with the aim of designing and implementing a web-based expert system to assist teachers in efficiently identifying students' dominant learning styles. The use of this system is expected to improve the quality of the learning process by adjusting teaching strategies to match students' learning preferences. This alignment aims to create a more engaging and effective learning experience, support the development of adaptive instructional strategies, and ultimately enhance student participation and learning outcomes.

II. RELATED WORKS

A. Expert System

Expert systems are computer programs or information systems designed to emulate human expertise and knowledge in specific fields such as medicine, law, education, or engineering. These systems operate by utilizing a knowledge base and an inference engine to analyze data, draw conclusions, and provide recommendations based on predefined rules [13]–[15]. As a key component of artificial intelligence (AI) applications, expert systems enable individuals without specialized expertise to obtain accurate and efficient solutions. Their applications have expanded across various domains, including disease diagnosis in healthcare [16], learning style adaptation in education [17] and machine failure diagnosis in industry [18], demonstrating the effectiveness of expert systems in delivering timely and precise solutions.

B. Euclidean Probability

The Euclidean Probability method is used to calculate the likelihood of an event occurring by considering various relevant factors. Each factor is assigned a value of 1 if the condition occurs and 0 if it does not, and then calculated using the Euclidean formula with weights determined by experts. These weights reflect how closely the factor aligns

with the observed condition. In this method, Euclidean Probability is applied to generate diagnostic conclusions by utilizing the knowledge data stored in the expertise database [19]

C. Learning styles

Learning styles refer to the ways in which individuals receive, understand, process, and store new information, especially regarding challenging material [20]. Each individual has specific sensory or cognitive preferences that influence the effectiveness of their learning. The VARK model, developed by Neil Fleming, categorizes learning styles into four types: Visual, Auditory, Read/Write, and Kinesthetic [21]. This model is designed to assist educators in adjusting their teaching methods to better align with the individual preferences of students [22]. Based on the research conducted [23] most students exhibit a tendency toward a particular learning style. Recognizing their dominant style plays a key role in facilitating the learning process, as it enables educators to design appropriate instructional models and select media that suit students' characteristics. Furthermore, studies show that the application of the VARK model can improve academic outcomes, as teaching methods aligned with learners' natural preferences are more effective in enhancing comprehension and fostering greater engagement.

III. METHODOLOGY

In this system development, a flowchart is used to represent the process flow, from data collection to learning style recommendations, ensuring clear understanding. The Waterfall method is chosen for its structured approach, fitting the research's need for clear, sequential stages [24]. The research follows systematic steps, detailed in Figure 1.

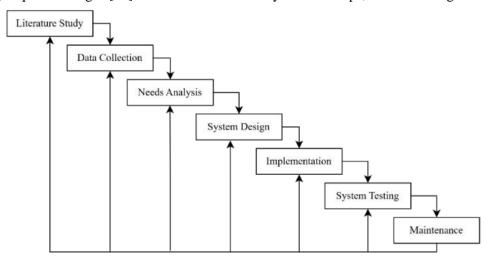


Figure 1. Waterfall development stages

A. System Scheme

The system schema illustrates the workflow of the expert system designed to identify student learning styles. The process begins with inputting data on learning style characteristics into a knowledge base that contains decision-making rules. Next, the system calculates data proximity using the Euclidean Probability method based on the VARK (Visual, Auditory, Read/Write, Kinesthetic) model. The results of this calculation are then used to determine the dominant learning style and provide recommendations for appropriate learning methods. The entire process, from data input to final recommendations, is illustrated in the system flow diagram shown below, which demonstrates the application of the Euclidean method in the learning style determination system.

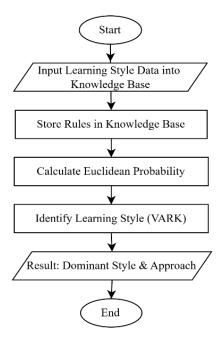


Figure 2. System Scheme

B. Euclidean Probability Method

The system schema illustrates the workflow of the expert system in identifying student learning styles. The process begins with inputting data on learning style characteristics into a knowledge base that contains decision-making rules. Next, the system calculates data proximity using the Euclidean Probability method based on the VARK (Visual, Auditory, Read/Write, Kinesthetic) model. The results of this calculation are used to determine the dominant learning style and provide recommendations for appropriate learning methods. The system flow scheme using the Euclidean method is shown in Figure below:

1. Identification of Symptom Conditions and Evidence Weights.

In the application of this method, value determination based on [25], is done by assigning a score of 1 when a factor meets the specified criteria, and a score of 0 when it does not, as shown in Table 1 below.

Table 1. Condition Description

No Condition Description Value

1 Yes 1
2 No 0

The determination of evidence weight (NBE_i) occurs at the data analysis stage to assess the relevance of each symptom to the condition, using a scale from 0 to 1. A value approaching 1 indicates that the symptom more accurately represents the condition in question.

2. Euclidean Probability (EP) Calculation.

The calculation of the EP value is performed to assess the degree of relevance between the observed symptoms and the specified condition [26]. The EP value is computed using the following formula:

$$EP = \sqrt{(E_1 * NBE_1)^2 + (E_2 * NBE_2)^2 + ... (E_n * NBE_n)^2}$$
 (1)

3. Convert Distance to Probability.

The distance calculated in the Euclidean space is subsequently converted into a probability value, reflecting the likelihood of the observed symptoms corresponding to the specified condition.

$$P(x,y) = \frac{1}{1 + EP}$$
 (2)

4. Decision Making.

Based on the computed probability, a decision is made regarding the relevance of the condition to the observed symptoms.

IV. RESULT AND DISCUSSION

This section outlines the methodology and steps for implementing the Euclidean Probability method to identify learning styles, focusing on both the website-based system and manual calculations. This approach ensures accurate and personalized recommendations for learning strategies.

A. Analysis of System Requirements

The knowledge obtained from interviews was transformed into a table of learning styles and their characteristics, which serves as the system's knowledge base to facilitate the solution-finding process. This table of learning style types and associated characteristics functions as a pattern-matching reference between user input and the knowledge base. The characteristics were validated by psychological experts Dwi Iramadhani, S.Psi., M.Psi., Psychologist, Taifatul Jannah, M.Psi., Psychologist and Nursan Junita, B.H.Sc., M.A. and used as the basis for assigning weight values through expert judgment. The table below contains information about the different types of learning styles.

Tabel 2. Learning Modality

Code Learning Modality

T01 Visual

T02 Auditory

T03 Read/Write

T04 Kinesthetic

The table below presents the key characteristics representing the four VARK learning styles: Visual, Auditory, Read/Write, and Kinesthetic. Each learning style reflects different preferences in how individuals absorb, process, and retain information.

Tabel 3. Characteristics

Code	Learning Style Characteristics	Weight
K01	Information retention is enhanced through visual representations such	
	as images and diagrams.	0.92
K02	Utilizing color coding and highlights improves the effectiveness of	
	note-taking.	0.92
K03	A stronger preference is shown for reading textual materials over	•
	auditory explanations.	0.75
K04	Visual clutter adversely affects concentration during learning	
	activities.	0.92
K05	Facial recognition is superior to name recall in memory retention.	0.75
K06	Specific color schemes are consistently employed to systematically	
	categorize information.	1
K07	Learning outcomes are optimized through auditory exposure.	0.92
K08	Self-verbalization strategies are frequently applied to reinforce	
	comprehension.	0.83

K09	Environmental noise substantially impairs concentration during the	_
	learning process.	1
K10	Engaging in collaborative discussions promotes deeper understanding	
	and knowledge consolidation.	0.75
K11	Individuals exhibit a stronger recall for names compared to facial	
	recognition.	1
K12	Verbal explanations are processed more effectively than written	
	information.	0.92
K13	Rewriting learning materials in one's own words enhances knowledge	
	internalization.	0.92
K14	A clear preference for text-based resources is demonstrated over oral	
	instructions.	0.92
K15	Study materials are systematically organized using structured outlines	
	and lists	0.83
K16	Detailed and organized note-taking practices enhance the learning	
	process.	1
K17	Written instructions are more effectively comprehended than verbal	
	explanations.	1
K18	Supplementary reading from articles and books is actively pursued to	
	deepen subject comprehension.	1
K19	Learning is enhanced through direct, hands-on experiential activities.	0.83
K20	Incorporation of physical movement during study sessions to	
	maintain focus.	0.92
K21	Difficulty remaining seated for extended periods while studying.	0.83
K22	Physical activity contributes to improved learning outcomes.	0.92
K23	Gestural communication frequently accompanies verbal exchanges.	0.92
K24	Active participation in experiments and simulations is preferred for	
	effective knowledge acquisition.	0.92

The table below contains the rules for each learning style characteristic that will be used in the knowledge base applied to the system.

Tabel 4. Knowledge base rules

Code	Learning Modality	Characteristics
R01	Visual (T01)	IF K01 AND K02 AND K03 AND K04 AND K05 AND K06 THEN T01
R02	Auditory (T02)	IF K07 AND K08 AND K09 AND K10 AND K11 AND K12 THEN T02
R03	Reading/ Writing (T03)	IF K13 AND K14 AND K15 AND K16 AND K17AND K18 THEN T03
R04	Kinesthetic (T04)	IF K19 AND K20 AND K21 AND K22 AND K23 AND K24 THEN T04

B. Calculation of Euclidean Probability

In this stage, the calculation of values to determine learning styles will be performed using Euclidean Probability. Below is the Euclidean Probability calculation for the case example that has been analyzed.

Table 5. Case Data

No	Learning Style Characteristics	Weight
1	Information retention is enhanced through visual representations such as	0.92

	images and diagrams (K01).	
2	Facial recognition is superior to name recall in memory retention (K05).	0.75
3	Learning outcomes are optimized through auditory exposure (K07),	0.92
4	Environmental noise substantially impairs concentration during the	
	learning process (K09).	1
5	Engaging in collaborative discussions promotes deeper understanding and	
	knowledge consolidation (K10).	0.75
6	Verbal explanations are processed more effectively than written	
	information (K12).	0.92
7	Learning is enhanced through direct, hands-on experiential activities	
	(K19)	0.83
8	Incorporation of physical movement during study sessions to maintain	
	focus (K20)	0.92
9	Difficulty remaining seated for extended periods while studying (K21)	0.83
10	Gestural communication frequently accompanies verbal exchanges (K23)	0.92
11	Active participation in experiments and simulations is preferred for	0.92
	effective knowledge acquisition (K24).	

The steps to solve the case using the Euclidean Probability method are as follows:

1. Determine the Condition Values

The condition values are obtained from the characteristics experienced, and the data for the condition weight values can be seen in the table 1.

2. Calculate the Probability Values

learning style Visual:

$$T01 = \sqrt{(1*0.92)^2 + (0*0.92)^2 + (0*0.75)^2 + (0*0.92)^2 + (1*0.75)^2 + (0*1)^2} = 1,187$$
 learning style Auditory:

$$T02 = \sqrt{(1*0.92)^2 + (0*0.83)^2 + (1*1)^2 + (1*0.75)^2 + (0*1)^2 + (1*0.92)^2} = 1,804$$
 learning style Read/Write:

$$T03 = \sqrt{(0*0.92)^2 + (0*0.92)^2 + (0*0.83)^2 + (0*1)^2 + (0*1)^2 + (0*1)^2} = 0$$
learning style Kinesthetic:

$$T04 = \sqrt{(1*0.83^2) + (1*0.92)^2 + (1*0.83)^2 + (0*0.92)^2 + (1*0.92)^2 + (1*0.92)^2} = 1,979$$

The results of calculations using the Euclidean Probability method indicate that the dominant learning style is Kinesthetic, with a diagnostic value of 1.979, which has the highest probability compared to the Visual, Auditory, and Read/Write learning styles in the VARK model.

C. Learning Style Distribution Analysis

Based on the data processing results obtained from 110 students, which were analyzed using a web-based expert system with the Euclidean Probability method, the following distribution of dominant learning styles among the students was obtained: 32 students (29.09%) were identified with a Visual (V) learning style, 26 students (23.64%) with an Auditory (A) learning style, 16 students (14.55%) showed a preference for the

Read/Write (R) learning style, and 36 students (32.73%) had a dominant Kinesthetic (K) learning style.

These findings indicate that the Kinesthetic learning style is the most dominant among students at SMK Negeri 3 Lhokseumawe, followed by the Visual, Auditory, and Read/Write learning styles. This information is crucial for both students and educators in designing more adaptive learning strategies that align with the dominant learning styles of the students. Expert validation showed that the system achieved an accuracy rate of 92%, which demonstrates its reliability in accurately identifying students' dominant learning styles. Therefore, it is expected that these learning strategies will enhance the effectiveness and quality of the learning process within the school environment. The data distribution is further illustrated in Figure 3.

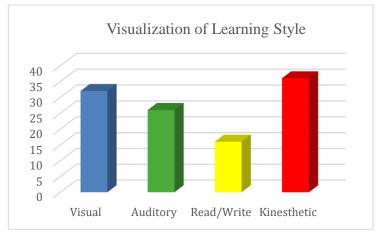


Figure 3. Diagram of Learning Style Distribution

D. Website Implementation

This expert system is developed as a web-based application using PHP and MySQL to identify students' learning styles through the Euclidean Probability method. The system consists of a landing page for student data input and an admin dashboard for managing results and the knowledge base. It helps automatically determine learning styles and supports the implementation of appropriate teaching methods.

1. Home Page

The main page is the initial display of the expert system for identifying students' learning styles, providing access to the homepage, learning style information based on the VARK model, and a login feature for accessing advanced system functions.



Figure 4. Home Page

2. Login Page

The login page serves as an access point for both administrators and users according to their respective roles, allowing administrators to access the admin dashboard and general users to access available features. The login page interface is shown in the following image.



Figure 5. Login Page

3. Administrator Page

The administrator dashboard provides a summary of system data, including the number of users, symptoms, learning style categories, and consultation history. Admins can manage user information, update rules, and customize learning style characteristics to maintain system accuracy as shown in the figure below.

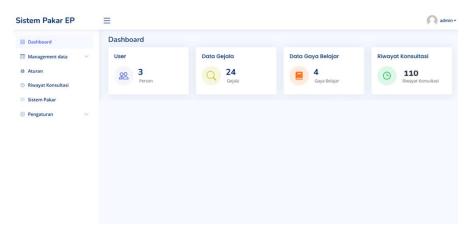


Figure 6. Administrator Page

4. Consultation Page

The learning style consultation page allows users to select the characteristics that best match their learning style and click the process button to obtain the identification result of the dominant learning style. The consultation results are displayed as shown in the figure below.

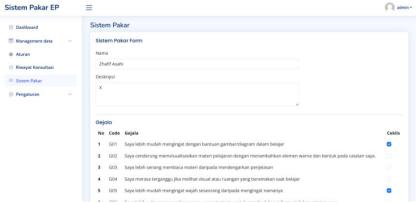


Figure 7. Consution Page

5. Consultation Results Page

The results page displays the probability value of each learning style, which allows the system to determine the dominant learning style based on the user's choice. The system also provides recommended learning approaches and solutions. The consultation page is shown in the figure below.



Figure 8. Consultation Result Page

V. CONCLUSION

Based on a total of 110 student data analyzed using a web-based expert system with the Euclidean Probability method, the distribution of learning styles was as follows: 32 students (29.09%) were identified with a Visual (V) learning style, 26 students (23.64%) with an Auditory (A) style, 16 students (14.55%) with a Read/Write (R) style, and 36 students (32.73%) with a Kinesthetic (K) learning style. These results indicate that the majority of students at SMK Negeri 3 Lhokseumawe tend to have a Kinesthetic learning style, followed by Visual, Auditory, and finally Read/Write. Expert validation demonstrated that the system achieved an accuracy rate of 92%, proving its reliability in accurately diagnosing students' dominant learning styles. The designed expert system is capable of providing quick and accurate diagnoses, thereby assisting teachers in tailoring instructional strategies to suit individual student needs. Thus, the application of the Euclidean Probability method in this expert system has proven effective in systematically identifying students' learning styles and has the potential to enhance the learning process through a more personalized and adaptive teaching approach.

REFERENCES

- [1] R. R. Waliyansyah, M. Novita, dan L. P. Aditasari, "Sistem Pakar Penentuan Gaya Belajar Siswa Dengan Metode Forward Chaining Berbasis Web," *IT Journal Research and Development*, vol. 5, no. 1, pp. 32–44, Agustus 2020, doi: https://doi.org/10.25299/itjrd.2020.vol5(1).4740.
- [2] S. Subagja and B. Rubini, "Analysis of Student Learning Styles Using Fleming's VARK Model in Science Subject," *Jurnal Pembelajaran dan Biologi Nukleus*, vol. 9, no. 1, pp. 31–39, Mar. 2023, doi: https://doi.org/10.36987/jpbn.v9i1.3752.
- [3] J. A. Faruq, F. E. Melati, and M. Abadi, "Analisis Kolaborasi Gaya Belajar dalam Penerapan Pembelajaran Berdiferensiasi Kelas X SMA Negeri 1 Singosari," *Pedagogika: Jurnal Ilmu-Ilmu Kependidikan*, vol. 4, no. 2, pp. 115–120, 2024, doi: https://doi.org/10.57251/ped.v4i2.1538.
- [4] S. G. P. Kannappan, R. Doraisamy, and V. Jagadesan, "Assessment of Learning Styles of First-year Medical Students' using VARK 8.02 Model Questionnaire: A Cross-sectional Study," *Journal of Clinical and Diagnostic Research*, Jan. 2025, doi: https://doi.org/10.7860/jcdr/2025/74835.20557
- [5] B. L. Maknunin and D. Fitrayati, "Pengaruh Kejenuhan Belajar Peserta Didik dan Gaya Mengajar Guru terhadap Minat Belajar Peserta Didik," *Jurnal Pendidikan Ekonomi (JUPE)*, vol. 12, no. 2, pp. 322–329, 2024, doi: https://doi.org/10.26740/jupe.v12n2.p322-329.
- [6] R. H. S. Isna and T. Ardiansyah, "Implementasi Forward Chaining untuk Mendeteksi Kerusakan Komputer," *Jurnal Sistem dan Teknologi Informasi Indonesia (JUSTINDO)*, vol. 9, no. 1, pp. 46–54, Feb. 2024, doi: https://doi.org/10.32528/justindo.v9i1.1224.
- [7] S. Hardianti, A. Tenriawaru, and N. Ransi, "Sistem Pakar Diagnosa Penyakit Menular Pada Anak Menggunakan Metode Forward Chaining dan Backward Chaining," *JUST TI (Jurnal Sains Terapan Teknologi Informasi)*, vol. 13, no. 2, pp. 111–120, Jul. 2021, doi: https://doi.org/10.46964/justti.v13i1.607
- [8] N. Cangera, Y. Amaliah, and R. Gusmana, "Perbandingan Metode Euclidean Probability dan Teorema Bayes untuk Diagnosa Penyakit Gigi," *Journal of Big Data Analytic and Artificial Intelligence*, vol. 6, no. 1, pp. 11–18, 2023.
- [9] M. A. Rohman and D. Arifianto, "Penerapan Metode Euclidean Probability dan Confusion Matrix dalam Diagnosa Penyakit Koi," *Jurnal Smart Teknologi*, vol. 2, no. 2, pp. 122–130, 2021.
- [10] A. H. Ramadhan, A. R. Febriansyah, R. M, and S. S. Susanti, "Penerapan Sistem Pakar Dengan Metode Euclidean Probability Untuk Mengidentifkasi Penyakit Pada

- Tanaman Singkong," *Jurnal Nasional Komputasi dan Teknologi Informasi (JNKTI)*, vol. 4, no. 4, pp. 253–257, Aug. 2021, doi: https://doi.org/10.32672/jnkti.v4i4.3103.
- [11] P. S. Ramadhan, "Penerapan Komparasi Teorema Bayes dengan Euclidean Probability dalam Pendiagnosaan Dermatic Bacterial," *InfoTekJar (Jurnal Nasional Informatika dan Teknologi Jaringan*), vol. 4, no. 1, pp. 1–7, 2019, doi: https://doi.org/10.30743/infotekjar.v4i1.1579.
- [12] N. F. Azhar, B. Prihasto, and N. R. N. Salsabila, "Expert System for Diagnosing Plant-disturbing Organisms on Rice Plants Using the Euclidean Probability Method and Bayes Theorem with Forward Chaining Inference Technique," *SPECTA Journal of Technology*, vol. 8, no. 3, pp. 250–260, 2024, doi: https://doi.org/10.35718/specta.v8i3.1255
- [13] M. I. R. Hasibuan, "Sistem Pakar Mendiagnosa Penyakit ITP (Idiopathic Thrombocytopenic Purpura) Menggunakan Metode Variable Centered Intelligent Rule System (VCIRS)," *Jurnal Sistem Komputer dan Informatika (JSON)*, vol. 1, no. 2, pp. 94–100, 2020, doi: https://doi.org/10.30865/json.v1i2.1954.
- [14] P. R. Ananda and Sriani, "Sistem Pakar Diagnosis Stunting pada Balita Menggunakan Metode Forward Chaining dan Logika Fuzzy Sugeno," *Jurnal Teknologi Sistem Informasi dan Aplikasi*, vol. 7, no. 1, pp. 200–216, Jan. 2024, doi: https://doi.org/10.32493/jtsi.v7i1.38245
- [15] M. Mahendra, R. Pane, and R. Rohani, "Analisis Perbandingan Sistem Pakar dalam Mendiagnosa Penyakit Limfoma Hodgkin Menggunakan Algoritma Teorema Bayes dan Certainty Factor," *Building of Informatics, Technology and Science (BITS)*, vol. 5, no. 1, pp. 327–335, Jun. 2023, doi: https://doi.org/10.47065/bits.v5i1.3560.
- [16] M. Qamal, D. Hamdhana, and M. Martin, "Sistem Pakar untuk Mendiagnosa Penyakit Angina Pektoris (Angin Duduk) dengan Metode Forward Chaining Berbasis Web," *Techsi*, vol. 12, no. 1, 2020. doi :https://doi.org/10.29103/techsi.v12i1.2150
- [17] P. A. W. Purnama, T. A. Putra, R. Afira, dan O. E. Putra, "Sistem Pakar untuk Mengetahui Gaya Belajar Anak Menggunakan Metode Forward Chaining," *REMIK: Riset dan E-Jurnal Manajemen Informatika Komputer*, vol. 6, no. 2, pp. 124–129, 2022, doi: https://doi.org/10.33395/remik.v6i2.11359.
- [18] R. Noviardi, "Sistem Pakar Berbasis Web Menggunakan Metode Forward Chaining dalam Menganalisa Kerusakan Mesin Fotokopi dan Penanggulangannya (Studi Kasus di Q-EL Copier Service Center and Distributor)," *JURTEKSI (Jurnal Teknologi dan Sistem Informasi)*, vol. 6, no. 2, pp. 163–172, Apr. 2020, doi: https://doi.org/10.33330/jurteksi.v6i2.548.
- [19] R. S. Ramadhan, J. Hutagalung, and Y. Syahra, "Comparison of Knowledge-Based Reasoning Methods to Measure the Effectiveness of Diagnostic Results," *Journal of Physics: Conference Series*, vol. 1783, no. 1, p. 012049, Feb. 2021, IOP Publishing, doi: https://doi.org/10.1088/1742-6596/1783/1/012049.
- [20] S. R. Dewi and F. Yusri, "Pemahaman Wali Kelas Tentang Gaya Belajar Siswa," *Educatum: Jurnal Ilmu Pendidikan*, vol. 2, no. 1, pp. 1-8, 2023.
- [21] N. A. Chaudhry, A. Ashar, and A. A. Syeda, "Association of visual, auditory, read/write, and kinesthetic (VARK) learning styles and academic performances of dental students," *Pakistan Armed Forces Medical Journal*, no. 1, p. S58, 2020.
- [22] E. El-Saftawy, A. A. A. Latif, A. M. ShamsEldeen, et al., "Influence of applying VARK learning styles on enhancing teaching skills: application of learning theories," *BMC Med Educ.*, vol. 24, p. 1034, 2024, doi: https://doi.org/10.1186/s12909-024-05979-x.
- [23] R. Rafiska and R. Susanti, "Analisis Profil Gaya Belajar Peserta Didik Sebagai Data Pembelajaran Berdiferensiasi di Kelas XII SMA Negeri 1 Palembang,"

- *Research and Development Journal of Education*, vol. 9, no. 1, pp. 474-482, Apr. 2023, doi: https://doi.org/10.30998/rdje.v9i1.17043.
- [24] A. Sutikno, "Sistem Informasi Penggajian Karyawan PT Metagra Menggunakan Metode Waterfall," *Jurnal Publikasi Ilmu Komputer Dan Multimedia*, vol. 1, no. 2, pp. 100-110, 2022.
- [25] P. S. Ramadhan, "Penerapan Euclidean Probability dalam Mendiagnosis Atopik Dermatis," *Jurnal Teknologi Informasi dan Ilmu Komputer (JTIIK)*, vol. 7, no. 5, pp. 887-894, Oct. 2020. doi: https://doi.org/10.25126/jtiik.202072023.
- [26] P. S. Ramadhan, "Penerapan Probability Euclidean dalam Pendeteksian Penyakit Impetigo," *CESS (Jurnal Ilmu dan Sistem Rekayasa Komputer)*, vol. 4, no. 1, p. 11, Jan. 2019.