



CLASSIFICATION OF STUDENTS' ACADEMIC COMPETENCIES USING THE K-NEAREST NEIGHBOR (KNN) METHOD AT STATE VOCATIONAL HIGH SCHOOL 2 MEDAN

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imeldasridumayanti.sinaga@gmail.com**Abstract**

The Vocational Competency Test (UKK) is an evaluation instrument to determine the level of competency mastery of Vocational High School (SMK) students. However, the process of determining student eligibility to participate in the UKK is still carried out conventionally, so it takes a relatively long time and risks causing inconsistencies in the assessment. This study applies the K-Nearest Neighbor (KNN) algorithm to group students' academic competencies into two classifications: Ready to Participate in the UKK and Not Ready to Participate in the UKK. The data used comes from a 15-item knowledge aspect questionnaire given to 78 students majoring in Electrical Power Installation Engineering (TITL) at SMK Negeri 2 Medan. The data is separated into 62 training data or 80% and 16 test data or 20%. The data processing stage begins with preprocessing through Min-Max transformation and normalization. Next, classification is carried out using KNN with $K = 3$ and Euclidean Distance as the distance measurement method. Model performance is analyzed through a Confusion Matrix based on Accuracy, Precision, Recall, and F1-Score. The test yielded an accuracy of 81.25%, precision of 76.92%, recall of 100%, and an F1-score of 86.96%. These findings demonstrate that the KNN algorithm can be effectively used to identify students' academic competency readiness levels for the UKK. Furthermore, the developed web-based system can assist teachers in identifying students' readiness levels more quickly, systematically, and objectively as a basis for decision-making in facing the Skills Competency Test (UKK).

Keywords: K-Nearest Neighbor (KNN), Academic Competence, Expertise Competency Test (UKK), Classification, Machine Learning, Confusion Matrix.

Introduction

The Vocational Competency Test (UKK) is an assessment instrument used to determine the level of competency mastery of Vocational High School (SMK) students based on their areas of expertise. For Electrical Power Installation Engineering (TITL) students at SMK Negeri 2 Medan, the UKK plays a strategic role in identifying mastery of vocational knowledge and skills. Students' readiness is determined by their mastery of the material, the intensity of their practical experience, and the learning they have undergone. The integration of theoretical learning, practical experience, and exam simulations can support competency improvement while building students' readiness and confidence in participating in the UKK. (Pekayunan Pengabdian et al., 2025) Therefore, efforts are needed to determine the level of student readiness before the UKK so that students who experience difficulties can be provided with guidance and material reinforcement.

Assessment of readiness in the knowledge aspect is generally conducted through instruments or questionnaires, the results of which are summarized and analyzed. If conducted manually on a large number of students, this process is time-consuming and can be difficult to identify data patterns. The use of machine learning can be an alternative to help process student data and classify it based on patterns found in the data.(Wulansari et al., 2025)A data-driven approach can also help with the evaluation and decision-making stages more systematically (Ramadana et al., 2025).

One classification approach that can be applied is K-Nearest Neighbor (KNN), which is a supervised learning algorithm that identifies the category of new data by considering its level of similarity to a number of training data whose class labels are known.(Nuraeni et al., 2023)This method has been proven to provide optimal accuracy in predicting student graduation categories, making it suitable for use as an approach in academic decision-making.(Halimukid, 2026)Previous research also indicates that KNN is relevant for use in helping predict students' readiness to face the UKK.(IP Sari, 2024). In addition, KNN successfully grouped students' academic abilities objectively through a web-based system.(Indah Wahyuni & Kurniawan R., 2025).The results of this study indicate that KNN is relevant to be applied to the classification of students' academic competency data.

This study uses data from the knowledge aspect instrument given to students of grades XI TITL 2, XI TITL 3, and XI TITL 4 at SMK Negeri 2 Medan. The instrument consists of 15 questions related to vocational competencies in the UKK. Students' answers are processed into numerical values to determine the categories of Ready to Take the UKK and Not Ready to Take the UKK. A total of 78 student data were used as the dataset, then divided into 80% training data of 62 data and 20% test data of 16 data. Before classification using KNN, the data went through a preprocessing and normalization stage to support the calculation of Euclidean distance.

RESEARCH METHODS

This study uses a data mining and supervised learning approach by applying the K-Nearest Neighbor (KNN) algorithm to classify students' academic competency levels in the knowledge aspect into two categories, namely Ready to Take the UKK and Not Ready to Take the UKK. The research object focuses on students majoring in Electrical Power Installation Engineering (TITL) at SMK Negeri 2 Medan. Data were collected through a test instrument or knowledge questionnaire in the form of 15 structured questions based on vocational material. Answers from 78 students were collected through Google Forms and measured objectively with a score weighting of 1 to 5. The total score for each student was obtained from the sum of the instrument scores, then labeled readiness. Students with a total score of 63 and above were categorized as Ready to Take the UKK, while scores below 63 were categorized as Not Ready to Take the UKK.

The entire dataset of 78 student data was then partitioned with a proportion of 80% as training data of 62 data and 20% as test data of 16 data. Before the classification process was run, the data first went through a preprocessing stage in the form of value transformation into numeric form and data normalization. The method used was Min-Max Normalization to change the range of attribute values into intervals of 0 to 1. This stage is very crucial so that each question attribute has a balanced contribution and

weight in the distance calculation, thus avoiding the dominance of a certain value scale.

After the data was normalized, the KNN modeling process was carried out by measuring the distance between each test data and all training data using the Euclidean Distance calculation based on 15 question attributes. The results of the distance calculation were then sorted from smallest to largest to determine the nearest neighbors. Classification testing was evaluated at several variations of odd K values, namely $K = 3$, $K = 5$, $K = 7$, $K = 9$, and $K = 11$. The final classification was determined based on a majority voting mechanism from the most dominant class among the K nearest neighbors. From this testing, the value of $K = 3$ was selected as the best model parameter because it produced an optimal level of performance. Model performance evaluation was systematically measured using a Confusion Matrix that calculates Accuracy, Precision, Recall, and F1-Score metrics. All these stages were built and presented through a web-based system to facilitate a structured analysis of student readiness.

Research results

System implementation is the process of translating the design into a web-based application to identify students' readiness for the Skills Competency Test (UKK) using the K-Nearest Neighbor (KNN) algorithm. The application utilizes the PHP programming language and the Bootstrap framework for the interface, enabling the system to be run through a web browser with a responsive and practical design.

The implementation follows the research stages in Chapter III, which include reading the dataset, separating training data and test data, normalization using the Min-Max method, measuring distance with Euclidean Distance, classification using the K-Nearest Neighbor algorithm, and testing model performance using the Confusion Matrix.

The system is designed with a simple usage mechanism, namely the user simply enters a CSV-formatted dataset and sets the K value. After the parameters are determined, the system runs the entire classification process automatically and presents training data, test data, prediction results, and model evaluation metrics.

System Home Page

The main page is the initial interface of the application, used by users to perform the classification process. This page provides a form for uploading a dataset in CSV format and inputting the K value used as a parameter in the K-Nearest Neighbor algorithm. The system's main page is shown in Figure 4.1.

Figure 4.1 System Home Page

Based on Figure 4.1, the application's main page has a simple interface, making it easy for users to perform the classification process. Users simply need to select the dataset file to be used and then enter the K parameter value according to their research needs. Once all the data is entered, the classification process is executed by pressing the KNN process button.

The K parameter is the number of nearest neighbors used as the basis for decision-making in the K-Nearest Neighbor algorithm. In this study, a value of $K = 3$ was used, in accordance with the predetermined test scenario.

Data Set Reading Implementation

After the user selects a dataset and presses the Process KNN button, the system reads the uploaded CSV file. Each row of data is processed using PHP's CSV read function and then saved to an array as the primary dataset for use in the classification process.

The research dataset consists of student identities and fifteen question attributes (Q1 to Q15) obtained from completing the UKK readiness instrument. Furthermore, the system calculates each student's total score as the basis for determining class labels: Ready to Take the UKK or Not Ready to Take the UKK.

The system then displays information regarding the amount of data successfully read, the amount of training data, the amount of test data, and the K parameter value used in the classification process. The dataset information image is presented in Figure 4.2.



Figure 4.2 Dataset Information

Data Normalization Implementation

The next step is the data normalization process, applying the Min-Max Normalization method. This process aims to equalize the value ranges of all attributes so that no attribute has a greater influence than another in the distance calculation process.

In system implementation, the minimum and maximum values are calculated based on the training data and then used to normalize both the training and test data. This approach was chosen to prevent data leakage in the classification process, which is when information from the test data is used in the model learning process.

The normalization methods used are:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}$$

with:

X' = normalized result value,

X = original value of attribute,

X_{min} = minimum attribute value,

X_{max} = maximum attribute value.

Normalization results in the transformation of the values of all attributes into a scale of 0 to 1, so that each attribute has a relatively equal contribution weight in the Euclidean Distance calculation process. The normalized data results on the training data are shown in Table 4.1, while the test data are presented in Table 4.2.

Table 4.1 Training Data Normalization

Data	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9
L1 (D12)	00.05	00.25	1	1	00.05	00.05	4.62986 1111	00.25	0.0520 83333
L2 (D56)	0	0.0520 83333	0.0520 83333	1	00.25	1	1	0.0520 83333	0.0520 83333
L3 (D24)	00.05	00.25	00.05	0.0520 83333	00.05	1	4.62986 1111	0.0520 83333	0.0520 83333
L4 (D22)	1	0.0520 83333	0.0520 83333	1	00.05	00.05	1	1	0.0520 83333
L5 (D28)	1	0.0520 83333	0.0520 83333	1	0	00.05	4.62986 1111	00.25	1
L6 (D32)	1	1	0.0520 83333	00.25	00.05	1	1	0.0520 83333	00.05
L7 (D27)	1	0	1	0.0520 83333	0	1	4.62986 1111	1	0.0520 83333
L8 (D9)	00.05	00.25	0.0520 83333	0.0520 83333	0.0520 83333	1	4.62986 1111	1	1
L9 (D60)	0.0520 83333	00.25	1	0.0520 83333	0	1	1	0.0520 83333	0.0520 83333
L10 (D66)	1	0.0520 83333	1	1	1	1	1	1	0.0520 83333
...	...	...	...	...	...	...	...	...	...
L62 (D23)	1	1	1	1	1	1	1	1	0.0520 83333
Q10	Q11	Q12	Q13	Q14	Q15	Score	Normalization (Score)	Label	
4.6298 61111	00.25	0.0520 83333	4.6298 61111	0.0520 83333	1	55	3.28958 3333	Not ready	
4.6298 61111	1	1	1	1	1	63	4.75138 8889	Ready	
4.6298 61111	00.05	0.0520 83333	1	1	1	58	3.8375	Not ready	

0	00.05	0.0520 83333	4.6298 61111	00.05	2.3145 83333	58	3.8375	Not ready
0	0	00.05	2.3145 83333	0.0520 83333	1	52	2.74097 2222	Not ready
1	0.0520 83333	0.0520 83333	1	1	1	64	4.93402 7778	Ready
4.6298 61111	0.0520 83333	1	2.3145 83333	1	4.6298 61111	59	4.02013 8889	Not ready
1	0.0520 83333	1	4.6298 61111	1	1	64	4.93402 7778	Ready
1	00.05	1	4.6298 61111	1	1	61	4.38611 1111	Not ready
4.6298 61111	0.0520 83333	1	2.3145 83333	1	1	69	5.84791 6667	Ready
...	...	...	...	...	...	...	...	...
4.6298 61111	0.0520 83333	1	1	1	1	72	6.39652 7778	Ready



Table 4.2 Data Normalization Table

Data	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9
U1 (D49)	1	1	1	1	1	1	1	1	0.0520 8333
U2 (D33)	1	1	1	1	1	1	1	1	0.0520 8333
U3 (D7)	00.05	00.25	1	1	00. 05	00. 05	462.986.1 11	00.25	0.0520 8333
U4 (D67)	00.05	0	00.25	0	0	00. 05	462.986.1 11	0.0520 8333	00.25
U5 (D25)	0.0520 8333	1	1	1	1	1	1	1	0.0520 8333
U6 (D16)	00.25	1	1	0.0520 8333	1	1	1	1	0.0520 8333
U7 (D26)	0.0520 8333	0.0520 8333	0.0520 8333	1	00. 25	00. 05	231.458.3 33	1	0.0520 8333
U8 (D20)	00.05	0.0520 8333	0.0520 8333	0.0520 8333	00. 05	00. 05	462.986.1 11	00.25	1
...	...	...	...	...	...	...	...	...	...
U16 (D59)	1	1	1	1	1	1	1	1	0.0520 8333
Q10	Q11	Q12	Q13	Q14	Q15	Score	Normali zation (Score)	Label	
46.298 .611	0.0520 8333	1	462.98 6.111	1	1	71	649.652.7 78	Ready	
1	1	1	1	0.0520 8333	1	73	1	Ready	
46.298 .611	00.25	0.0520 8333	462.98 6.111	0.0520 8333	1	55	29.125	Not ready	
46.298 .611	00.25	0	231.45 8.333	1	1	42	0	Not ready	
1	1	1	1	1	1	73	1	Ready	
46.298 .611	0.0520 8333	1	462.98 6.111	1	- 0.3 333	63	470.416.6 67	Ready	
1	0.0520 8333	0.0520 8333	231.45 8.333	1	1	61	425.625	Not ready	
46.298 .611	00.05	0.0520 8333	231.45 8.333	00.25	1	54	268.819.4 44	Not ready	
...	...	...	...	...	...	...	...	...	
46.298 .611	0.0520 8333	1	462.98 6.111	1	1	71	649.652.7 78	Ready	

Table 4.2 shows the normalization results for 16 test data sets. The normalization process uses the minimum and maximum values obtained from the training data to prevent data leakage in the classification process. These normalization results are then used as input in the Euclidean Distance calculation.

Implementation of K-Nearest Neighbor Algorithm Calculation

After the normalization stage is complete, the system determines the proximity of each test data set to the entire training data set using a Euclidean distance calculation. The calculation is performed on fifteen normalized attributes, resulting in a distance value between each data set.

The Euclidean Distance equation used refers to the Euclidean Distance formula equation 2.2 as follows:

$$d(x, y) = \sqrt{\sum_{i=1}^n (x_i - y_i)^2}$$

with:

$d(x, y)$ = distance between test data and training data
 x_i = value of the i-th attribute in the test data
 y_i = value of the i-th attribute in the training data
 n = number of attributes

After all distances have been calculated, the system sorts the distance values from smallest to largest using a sorting function. Next, the $K = 3$ nearest neighbors with the smallest distance values are selected.

The system determines the predicted class based on majority voting, namely the category most found in the seven nearest neighbors will be the test result. The results of the K-Nearest Neighbor algorithm calculation are presented in Table 4.3. Table 4.3 K-Nearest Neighbor Algorithm Calculation Results

Table 4.3 shows that the system displays classification results for each test data set, including the actual label, predicted results, a list of nearest neighbors and their distances, and the classification status. This information makes it easier for users to understand the decision-making process carried out by the K-Nearest Neighbor algorithm.

System Evaluation Implementation

The final stage in system implementation is displaying the results of the classification model evaluation. After all test data has been predicted, the system compares the predictions with the actual labels to obtain True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) values.

These four components are used as the basis for calculating Accuracy, Precision, Recall, and F1-Score values. The calculations are performed automatically by the system based on the results of the Confusion Matrix. The system evaluation is presented in Figure 4.3.



Figure 4.3 System Evaluation

Based on Figure 4.3, the system successfully displayed the model evaluation results automatically after the classification process was completed. This information was used as a basis for determining the performance of the K-Nearest Neighbor algorithm in classifying students' readiness to participate in the UKK.

System Testing

System testing was conducted to identify the application's ability to classify students' readiness for the Skills Competency Test (UKK) using the K-Nearest Neighbor (KNN) algorithm. Testing was conducted after the entire implementation process was completed, starting with dataset reading, data division, normalization, distance calculation using Euclidean Distance, and the classification process using the majority voting method.

The dataset used in the testing consisted of 78 student data. The entire data set was then divided into 62 training data sets and 16 test data sets using a ratio of 80%=20%. The K parameter value used in this study was K=3, while the normalization method used Min-Max Normalization and the distance calculation used Euclidean Distance.

The test parameters used can be observed in Table 4.4.

Table 4.4 Testing Parameters

No	Parameter	Mark
1	Number of Datasets	78 Data
2	Training Data	62 Data
3	Test Data	16 Data
4	Algorithm	K-Nearest Neighbor
5	K value	3
6	Normalization Method	Min-Max Normalization
7	Distance Calculation Method	Euclidean Distance

Based on Table 4.4, the testing process was conducted using a single test scenario with a K value of 3. The training data served as a reference in the classification process, while the test data was used to measure the model's ability to predict student readiness classes. After the classification process was completed, the system compared the predicted results with the actual labels to obtain a Confusion Matrix value.

Test Results

The classification results obtained from the system were then evaluated using a Confusion Matrix. The Confusion Matrix was applied to identify the number of data points that the system successfully and unsuccessfully classified. The test results are presented in Table 4.5.

Table 4.5 Confusion Matrix

Actual/ Prediction	Ready to Take the UKK	Not Ready to Take the UKK
Ready to Take the UKK	10	0
Not Ready to Take the UKK	3	3

Based on Table 4.5, the True Positive (TP) value was 10 data, True Negative (TN) data was 3 data, False Positive (FP) data was 3 data, and False Negative (FN) data was 0 data. These values indicate that all students who were truly in the Ready to Take the UKK category were successfully recognized by the system. However, there were still 2 students who were actually in the Not Ready to Take the UKK category, but were predicted as Ready to Take the UKK.

In addition to the Confusion Matrix, the system also calculates model evaluation scores consisting of Accuracy, Precision, Recall, and F1-Score. The model evaluation results can be seen in Table 4.6.

Table 4.6 Model Evaluation Results

No	Evaluation Metrics	Mark	Results
1	Accuracy	0.8125	81.25%
2	Precision	0.7692	76.92%
3	Recall	1	100%
4	F1-Score	0.8696	86.96%

Based on Table 4.6, the Accuracy value was 81.25%, indicating that the system was able to correctly classify 14 of the 16 test data. The Precision value of 76.92% indicates that most of the data predicted as Ready to Take the UKK aligned with the actual conditions.

A 100% recall value indicates that all students in the Ready to Take the UKK category were successfully recognized by the system without any misclassification errors. Furthermore, an F1-score of 86.96% indicates that the model strikes a good balance between Precision and Recall, thus achieving good classification performance.

Test Data	Score	Normalization	7 Nearest Neighbors (ID, Distance)	Vote Ready	Vote Not Yet	Prediction	Original Label	Note
U1 (D49)	71	6.404.166.667	D17 (0), D64 (0.25), D58 (0.25), D4 (0.25), D65 (0.25), D50 (0.3333), D23 (0.3333)	7	0	Ready	Ready	✓
U2 (D33)	73	6.713.194.444	D40 (0.25), D34 (0.3536), D30 (0.3536), D42 (0.4167), D53 (0.433), D57 (0.433), D29 (0.4859)	7	0	Ready	Ready	✓
U3 (D7)	55	4.397.916.667	D12 (0), D5 (0.993), D24 (1.024), D60 (1.1335), D51 (1.2134), D74 (1.2191), D13 (1.2388)	1	6	Not yet	Not ready	✓
	42	2.854.861.111		0	7	Not yet		

U4 (D67)			D72 (1.3693), D18 (1.4767), D24 (1.5833), D62 (1.675), D12 (1.7638), D60 (1.7736), D51 (1.7834)			Ready	Not ready	✓
					0			
U5 (D25)	73	6.713.194.444	D40 (0.25), D34 (0.3536), D30 (0.3536), D42 (0.4167), D53 (0.433), D57 (0.433), D29 (0.4859)	7		Ready	Ready	✓
...	...	...	...	...	...	...	...	...
					0			
U16 (D59)	71	6.404.166.667	D17 (0), D64 (0.25), D58 (0.25), D4 (0.25), D65 (0.25), D50 (0.3333), D23 (0.3333)	7		Ready	Ready	✓

Discussion of Test Results

Test results indicate that the application has implemented all stages of the K-Nearest Neighbor algorithm according to the specified design. The system process includes loading the dataset, separating training and test data, normalizing using the Min-Max method, calculating Euclidean distance, implementing majority voting, and automatically performing model prediction and evaluation.

Based on the evaluation, the K-Nearest Neighbor algorithm demonstrated good classification capability on the research dataset, as reflected in its Accuracy score of 81.25%. This value indicates that the majority of the test data can be mapped to the correct class. Meanwhile, a Recall score of 100% indicates that the system successfully identified all students who were actually ready to take the UKK.

However, there were still three data points predicted as Ready to Take the UKK when they were actually in the Not Ready to Take the UKK category. This resulted in the Precision value falling short of 100%, at 76.92%. This misclassification indicates that some data points had characteristics quite similar to the Ready to Take the UKK class, so the K-Nearest Neighbor algorithm grouped them into that class based on the majority of nearest neighbors.

Overall, the test results indicate that the system has been able to implement the K-Nearest Neighbor algorithm well and produce adequate classification performance to assist the process of identifying students' readiness to take the Skills Competency Test (UKK).

Conclusion

Based on the findings of the study that has been carried out, it can be concluded that the questionnaire data measuring the knowledge aspects of students in the Electrical Power Installation Engineering (TITL) department at SMK Negeri 2 Medan has been successfully processed into a structured dataset for classification purposes. The data processing process includes data labeling, preprocessing, normalization using the Min-Max method, and separating the dataset into training data and test data as input for the K-Nearest Neighbor (KNN) algorithm. In addition, the KNN algorithm has been implemented in a web-based system to determine the category of students' academic competency readiness, namely Ready to Take the UKK and Not Ready to Take the UKK. Testing at a value of $K = 7$ resulted in an Accuracy level of 87.50%, Precision 83.33%, Recall 100%, and F1-Score 90.91%. These results indicate that the KNN method can be used effectively to support the process of identifying students' readiness in facing the Skills Competency Test (UKK).

References

- Affikri, M., Aruan, M. C., & Irsan, M. (2025). Penerapan Algoritma K-Nearest Neighbor untuk Prediksi Kelulusan Siswa di SD Negeri 1 Kedungsari. *Journal of Information System, Applied, Management, Accounting and Research*, 9(4), 1388. <https://doi.org/10.52362/jisamar.v9i4.2065>
- Halimukid, H. (2026). ANALISIS KELULUSAN SISWA MENGGUNAKAN METODE KNN (K-NEAREST NEIGHBOR) PADA DATASET "STUDENTS PERFORMANCE." *Jurnal Informatika dan Teknik Elektro Terapan*, 14(1). <https://doi.org/10.23960/jitet.v14i1.8384>

- Indah Wahyuni, U., & Kurniawan R., R. (2025). Algoritma K-Nearest Neighbor Classification Sebagai Sistem Pengelompokan Kemampuan Akademik Siswa Berbasis Web. *Decode: Jurnal Pendidikan Teknologi Informasi*, 5(2), 589–600. <https://doi.org/10.51454/decode.v5i2.1246>
- Nuraeni, S., Syam, S. P. A., Wajdi, M. F., Firmansyah, B., & Malkan, M. (2023). Implementasi Metode K-NN Untuk Menentukan Jurusan Siswa di SMAN 02 Manokwari. *G-Tech: Jurnal Teknologi Terapan*, 7(1), 89–95. <https://doi.org/10.33379/gtech.v7i1.1905>
- Palinggik Allorerung, P., Erna, A., Bagussahrir, M., & Alam, S. (2024). Analisis Performa Normalisasi Data untuk Klasifikasi K-Nearest Neighbor pada Dataset Penyakit. Dalam *Jurnal Informatika Sunan Kalijaga* (Vol. 9, Nomor 3).
- Pekayunan Pengabdian, J., Aplikasi Teknologi Digital untuk Masyarakat Berkelanjutan, dan, Keahlian Pada Jurusan Teknik Komputer Dan Jaringan Smk Al Amin, K. DI, & Rodi, M. (2025). *PENINGKATAN KESIAPAN SISWA SMK MELALUI PELATIHAN UJI ENHANCING THE READINESS OF VOCATIONAL HIGH SCHOOL STUDENTS THROUGH COMPETENCY TEST TRAINING (UKK) IN THE COMPUTER AND NETWORK ENGINEERING DEPARTMENT AT SMK AL-AMIN*. <https://pekayunan.stmiklombok.ac.id/index.php/pekayunan/>
- Rahmalisa, U., Zulkifli, A., Muhaimin, A., Hidayat, L., Sarjana, S., Informasi, S., & Pekanbaru, H. T. (2022). *PERANCANGAN DAN IMPLEMENTASI SISTEM INFORMASI AKADEMIK DI SEKOLAH DASAR ISLAM TERPADU BUSTANUL ULUM PEKANBARU BERBASIS WEB*. <https://doi.org/10.33060/JIK/2021/Vol11.Iss2.279>
- Ramadana, F. D., Pratama, W. P., & Lingga, C. (2025). *Implementasi Algoritma K-Means Clustering terhadap Tingkat Kepuasan Peserta LKP Multi Talenta Komputer Purwokerto*. 3.
- Sanjaya, A., & Wahyana, T. (2022). *PENERAPAN METODE K-NEAREST NEIGHBOUR UNTUK SISTEM PREDIKSI KELULUSAN SISWA MTS NURUL MUSLIMIN BERBASIS WEBSITE*. *Journal Transformation of Mandalika*, 3(1). <http://ojs.cahayamandalika.com/index.php/jtm/issue/archive>
- Sari, I. P. (2024). *Perbandingan Sistem Prediksi Menggunakan Metode Monte Carlo dengan Metode K-NN pada Nilai Peserta Didik Uji Kompetensi Kejuruan*.
- Sari, R., & Maiyana, E. (2023). *Sistem Informasi Akademik Berbasis Web di SDN 1 Rao Utara*.
- Setiawan, R., Rahayu, S., & Darul Ikhrom, T. (2025). Sistem Informasi Akademik Berbasis Web. *Jurnal Algoritma*, 22(2). <https://doi.org/10.33364/algoritma/v.22-2.1192>
- Sitompul, S., Manurung, S., Silalahi, A. P., Rumahorbo, B., & Silalahi, V. (2022). *METHOSISFO: Jurnal Ilmiah Sistem Informasi Sistem Informasi Reservasi Pada Monako Park Sibiru-Biru Berbasis Web* (Vol. 2, Nomor 1). <http://ojs.fikom-methodist.net/index.php/METHOSISFO>
- Wulansari, C., Dayanti, P. R., & Izazi, Z. Z. (2025). *Transformasi Digital dalam Pendidikan : Penerapan Algoritma Machine Learning dan Deep Learning untuk Meningkatkan Efektivitas Pembelajaran SMP*. 7(1), 877–885.