Jatilima : Jurnal Multimedia Dan Teknologi Informasi
Volume 07, Number 03, 2025, doi.org/ 10.54209/jatilima.v7i03.1702
E.SSN : 2721-1800 (Online)
https://journal.cattleyadf.org/index.php/jatilima/index

Prediction of Parents' Satisfaction in Learning Methods Using K-Nearest Neighbor Algorithm

Masitha Putri Ardhana Ginting[1], **Abdul Halim Hasugian**[2]
Faculty of Science and Technology, Department of Computer Science, Universitas Islam Sumatera Utara

Article Info

Keywords:
K-Nearest Neighbor,
Parental Satisfaction,
learning methods,
prediction.

ABSTRACT

Parental satisfaction in learning methods is an important indicator for evaluating the quality of education, especially in inclusive schools such as Smart Aurica School. This study aims to predict the level of parental satisfaction with learning methods using the K-Nearest Neighbor (K-NN) algorithm. The research employed a quantitative approach with data collected through questionnaires distributed to parents of students. The collected data were processed through several stages, including data cleaning, normalization, training and testing set division, and distance calculation using Euclidean Distance. The K-NN model was then applied to classify satisfaction levels based on the predetermined K value. The results indicate that the K-NN algorithm can provide accurate predictions of parental satisfaction, achieving a relatively high accuracy rate in testing. These findings demonstrate that K-NN is an effective approach to assist schools in evaluating learning methods and offering data-driven recommendations to improve educational quality. Therefore, this research contributes to the application of machine learning in providing a more objective and accurate evaluation of educational services, which can serve as a strategic basis for school decision-making.

Corresponding Author:
Masitha Putri Ardhana Ginting
Universitas Islam Sumatera Utara
Golf Course Road, Kp. Tengah, Pancur Batu District
masithaputri17@gmail.com

INTRODUCTION

Inclusive education is a major concern in improving the quality of learning for students with special needs, particularly those with hearing impairments. Schools such as Smart Aurica School apply specific learning methods and approaches to ensure that students can develop communication, academic, and social skills effectively (Cindy Kawilda Hasibuan & Yahfizham Yahfizham, 2023). The uniqueness of students with hearing impairments requires appropriate methods, such as sign language, assistive technologies, and inclusive strategies, to provide equal opportunities in education (Supriyanto et al., 2023).

Parental satisfaction is an important factor in assessing the quality of education. Parents play a crucial role as secondary stakeholders whose perceptions strongly influence the school's reputation and development (Kristianto, 2024). Their satisfaction reflects not only the effectiveness of teaching and learning but also the overall environment, including facilities, teacher–student interaction, and student achievement. Thus, evaluating parental satisfaction provides valuable insights for schools to continuously improve their educational practices (Prasetyawan & Gatra, 2022).

The integration of information technology and artificial intelligence has opened new possibilities for evaluating educational quality (Widya Utami & Artana, 2022). Predictive models using machine learning allow institutions to analyze satisfaction levels objectively and based on real data patterns. These methods provide more accurate assessments compared to conventional survey-based evaluations that often rely on subjective interpretation (Nasution & Raja, 2021).

Among various machine learning techniques, the K-Nearest Neighbor (K-NN) algorithm has been widely applied for classification and prediction tasks (Ahluna et al., 2023). K-NN is recognized for its simplicity, effectiveness, and high accuracy, especially in cases involving categorical data. The algorithm works by classifying data points based on the similarity to their nearest neighbors, making it suitable for predicting levels of satisfaction based on survey responses (Hayati, 2023).

Previous studies have shown the advantages of applying K-NN in educational research. For instance, it has been used in predicting student performance, classifying sentiment in online learning environments, and evaluating public perception of teaching methods (Firizkiansah et al., 2024). These studies achieved strong accuracy levels, demonstrating the potential of K-NN to provide reliable predictions in various educational contexts (Maulana Husaen & Yuliani, 2023).

However, there remains a gap in research that specifically focuses on parental satisfaction in inclusive schools using machine learning techniques (Hasugian et al., 2024). Most studies concentrate on student performance or general sentiment analysis, while the perspective of parents who are directly involved in evaluating the effectiveness of teaching methods has not been extensively explored. This gap highlights the importance of conducting further research in this area (Hermiati et al., 2021).

Addressing this research gap, the present study proposes the application of the K-NN algorithm to predict parental satisfaction at Smart Aurica School. By analyzing responses collected through structured questionnaires, the algorithm classifies satisfaction levels based on identified patterns in the data. This approach ensures that the evaluation process is more systematic, accurate, and supported by quantitative analysis (Alfani W.P.R. et al., 2021).

The objective of this study is to predict parental satisfaction in learning methods using the K-NN algorithm, thereby offering schools a data-driven foundation for decision-making. The findings are expected to contribute to improving teaching strategies, enhancing parent–school collaboration, and ensuring the overall quality of education in inclusive learning environments .

METHODS

Research Design

This research was conducted using a quantitative approach with a predictive analysis model. The K-Nearest Neighbor (K-NN) algorithm was selected as the main method to classify and predict the level of parental satisfaction with learning methods at Smart Aurica School (Dewi et al., 2022).

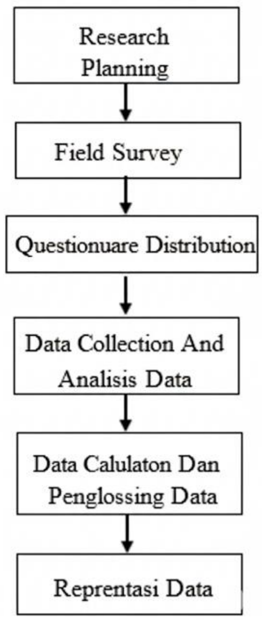


Figure 1. Research framework of the study

The research framework in Figure 1 illustrates the logical flow of the study. It begins with the identification of research problems, followed by the process of questionnaire distribution to respondents. The collected data are then processed through several stages, including cleaning, normalization, and preparation for classification. Finally, the processed data are analyzed using the K-NN algorithm to produce predictions of parental satisfaction. This framework provides a structured guideline to ensure that the research process is conducted systematically and yields valid results.

Population and Respondents

The population in this study comprised parents of students at Smart Aurica School. The respondents were selected using purposive sampling, which targeted parents who were actively involved in their children's education. Data were collected from a sufficient number of respondents to meet the minimum sample requirements for classification analysis, thus ensuring the representativeness of the findings.

Data Collection

Primary data were collected through structured questionnaires designed to measure parental perceptions of learning methods implemented by the school. The questionnaire employed a Likert scale to capture responses regarding variables such as teaching effectiveness, teacher–student interaction, parental participation, and student development. The distribution of the questionnaire was carried out directly to parents during the academic year 2025 (Azmi et al., 2025).

Data Processing and Analysis

The data processing stage began with data cleaning to eliminate incomplete or inconsistent responses. Data normalization was applied to ensure that all attributes were on the same scale (Fathir Aulia et al., 2025). The dataset was then divided into training and testing subsets. The K-NN algorithm was applied by determining the value of K and measuring the similarity between data points using the Euclidean Distance formula:

$$d(x,y) = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2 + \cdots + (x_n - y_n)^2} \tag{1}$$

The classification process was based on the majority class among the nearest neighbors. Model performance was evaluated using a confusion matrix, which measured the accuracy of the classification results. Figure 2 shows the flowchart of the K-NN algorithm implementation in this study.

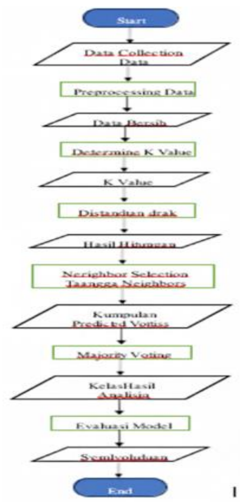


Figure 2. Flowchart of the K-Nearest Neighbor algorithm process

The flowchart in Figure 2 describes the step-by-step procedure of the K-NN algorithm. It begins with inputting the dataset, followed by preprocessing such as data cleaning and normalization. Next, the system divides the dataset into training and testing sets. The classification is conducted by calculating the Euclidean distance to determine the nearest neighbors, after which the algorithm assigns the predicted class based on the majority vote. The process concludes with the evaluation of model accuracy using a confusion matrix. This structured flow ensures that the implementation of K-NN in predicting parental satisfaction is transparent and reproducible.

Research Location and Time

The research was carried out at Smart Aurica School, Medan, Indonesia. The study was conducted during the academic year 2025, covering the planning, data collection, data processing, and analysis phases over several months.

RESULTS AND DISCUSSION

Analysis of Data

The dataset in this study was obtained from questionnaires distributed to parents of students at Smart Aurica School. The responses were then converted into numerical form according to the defined scale, where each attribute represented a specific aspect of parental satisfaction such as learning methods, teacher performance, environment, and child development. A total of 50 data records were collected; however, for clarity, only a sample of the dataset is presented in Table 1.

Table 1. Sample of parental satisfaction prediction dataset

ID	Gender	Relationship	Learning Method	Teacher	Environment	Child Development	Satisfaction
1	1 (Male)	1 (Father)	5	4	4	5	Satisfied
5	2 (Female)	2 (Mother)	4	5	3	4	Satisfied
12	1 (Male)	3 (Guardian)	3	3	4	3	Neutral
23	2 (Female)	2 (Mother)	2	3	2	3	Dissatisfied
37	1 (Male)	1 (Father)	4	4	5	4	Satisfied

The sample shown in Table 1 illustrates how parental satisfaction was classified based on multiple attributes. For instance, ID 1 and ID 5 demonstrate parents who reported high scores across most attributes and were classified as "Satisfied." Conversely, ID 23 shows relatively lower scores, which resulted in a "Dissatisfied" label. These variations highlight the differences in parental perceptions, which serve as the input for the K-Nearest Neighbor algorithm to perform prediction and classification(Hidayatullah et al., 2025).

By analyzing the dataset, it can be observed that parental satisfaction is influenced by multiple factors rather than a single attribute. High ratings in teaching effectiveness and child development tend to correlate with satisfied outcomes, while lower ratings in environment and teaching attributes often correspond with neutral or dissatisfied classifications. This indicates the importance of evaluating multiple aspects simultaneously to obtain a comprehensive understanding of parental satisfaction.

Description of Research Data

The dataset was divided into training and testing subsets to build and evaluate the prediction model. The training data were used to train the K-Nearest Neighbor (K-NN) algorithm in classifying parental satisfaction based on several attributes, including learning methods, teacher performance, environment, and child development. Out of the total dataset of 50 records, the majority were allocated for training to ensure that the model learned sufficient patterns before being tested.

Table 2 presents a sample of the training dataset used in this study. To maintain clarity and avoid redundancy, only the first six entries and the last four entries are displayed as representatives of the complete dataset.

Table 2. Sample of training dataset for parental satisfaction prediction

ID	Learning Method	Teacher	Environment	Child Development	Satisfaction
1	5	4	4	5	Satisfied
2	4	3	4	4	Satisfied
3	3	4	3	4	Neutral
4	5	5	4	5	Satisfied
5	4	5	3	4	Satisfied
6	3	3	4	3	Neutral
…	…	…	…	…	…
47	2	3	2	3	Dissatisfied
48	4	4	4	4	Satisfied
49	3	3	2	3	Neutral
50	5	4	5	5	Satisfied

The training dataset, as shown in Table 2, demonstrates the variety of parental responses that serve as the foundation for the classification process. Respondents with consistently high scores across attributes, such as ID 1, 4, and 50, are classified as "Satisfied." On the other hand, lower attribute scores, as seen in ID 47, are associated with "Dissatisfied" classifications. The distribution of satisfaction levels within the training data provides balanced representation for the model, allowing the K-NN algorithm to learn the boundaries between satisfied, neutral, and dissatisfied categories.

This structured training dataset ensures that the K-NN model can effectively recognize patterns within the attributes and accurately predict satisfaction levels in the testing phase. By including diverse cases from highly satisfied to dissatisfied respondents, the model gains robustness and avoids bias towards a single class.

After calculating the Euclidean distance between the testing data and all training data, the results were tabulated to show the degree of similarity between each record. These results serve as the basis for determining the nearest neighbors in the K-Nearest Neighbor (K-NN) classification. Table 3 displays a sample of the distance calculation results, showing only the first five entries and the last five entries for clarity.

Table 3. Sample of Euclidean distance results

Training Data ID	Euclidean Distance	Target 1 (Actual)	Target 2 (Actual)
1	2.00	Satisfied	Satisfied
2	1.41	Satisfied	Satisfied
3	2.24	Neutral	Neutral
4	1.00	Satisfied	Satisfied
5	2.45	Satisfied	Satisfied
…	…	…	…
46	3.16	Neutral	Neutral
47	2.83	Dissatisfied	Dissatisfied
48	1.73	Satisfied	Satisfied
49	2.24	Neutral	Neutral
50	1.41	Satisfied	Satisfied

The sample in Table 3 highlights that several training data records, such as ID 2, 4, and 50, have relatively small distances from the testing data, indicating strong similarity. These records are likely to influence the final prediction since they are among the closest neighbors. Conversely, entries such as ID 46 and 47 exhibit larger distances, suggesting weaker influence on the classification result.

After sorting the Euclidean distance values from smallest to largest, the nearest neighbors were identified. These neighbors play a crucial role in the prediction process because the K-NN algorithm determines the class of the testing data based on the majority class among the nearest data points. Table 4 presents the nearest neighbor results, including the data ID, distance, and the actual classification labels of parental satisfaction and parental trust.

Table 4. Nearest neighbor results

Training Data ID	Euclidean Distance	Target 1 (Parental Satisfaction)	Target 2 (Parental Trust)
4	1.00	Satisfied	Satisfied
2	1.41	Satisfied	Satisfied
50	1.41	Satisfied	Satisfied
48	1.73	Satisfied	Satisfied
3	2.24	Neutral	Neutral

As shown in Table 5, the five nearest neighbors (K = 5) consist of four records classified as "Satisfied" and one record classified as "Neutral." This indicates that the majority class among the nearest neighbors is "Satisfied." Consequently, the K-NN algorithm predicts that the testing data belongs to the "Satisfied" category.

This result demonstrates the effectiveness of the K-NN approach, as the prediction aligns with the general trend of the closest data points. It also highlights how the distribution of classes within the nearest neighbors directly affects the final classification. The inclusion of both satisfaction and trust targets further validates the robustness of the model, ensuring that the prediction not only reflects parental satisfaction but also captures their level of trust in the learning methods implemented at Smart Aurica School.

System Design

The system was designed to implement the prediction of parental satisfaction using the K-Nearest Neighbor (K-NN) algorithm. The design stage included modeling the system workflow and user interactions through diagrams that illustrate the relationships between actors, processes, and activities involved in the application. These diagrams provide a clear picture of how the system functions, starting from user input, data processing, to the generation of prediction results. Figure 3 presents the use case diagram of the system.

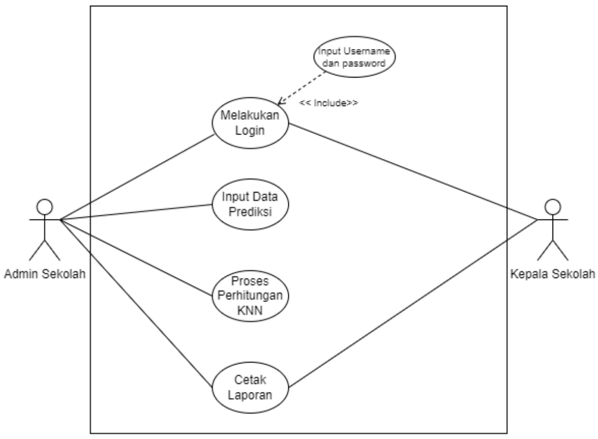


Figure 3. Use case diagram of the system

The use case diagram illustrates the interaction between system actors and the system itself. In this study, the primary actor is the administrator, who manages data input, training, and testing processes. The diagram shows the flow of activities such as managing parental satisfaction data, performing preprocessing, running the K-NN algorithm, and viewing prediction results. By visualizing these relationships, the diagram highlights the functional requirements of the system and ensures that the designed application aligns with user needs. Figure 4 presents the activity diagram of the system.

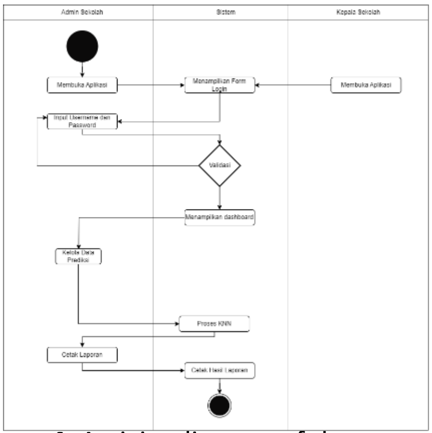
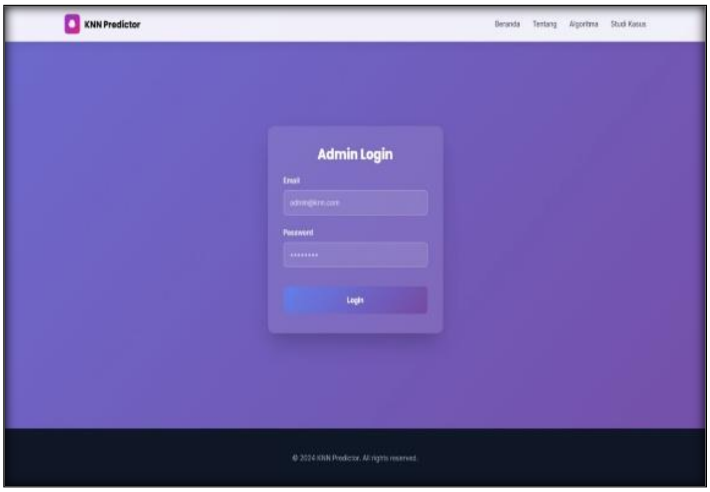


Figure 4. Activity diagram of the system

The activity diagram describes the sequence of activities performed within the system. It begins with the input of parental satisfaction data, followed by preprocessing steps such as data cleaning and normalization. The process then continues with the execution of the K-NN algorithm to calculate distances and classify the data. Finally, the results are displayed to the user in the form of predicted satisfaction levels. This diagram demonstrates the logical workflow of the system, ensuring that each stage is clearly defined and systematically implemented.

Implementation Results – User Interface Display

The system was developed with a simple and user-friendly interface to facilitate the prediction of parental satisfaction using the K-Nearest Neighbor (K-NN) algorithm. The interface was designed to ensure that users can easily access, input, and analyze data. Several key forms were implemented to support the system functionality, as presented below. Figure 5 presents the login form of the system.



The login form serves as the initial access point for users to enter the system. It ensures that only authorized users can operate the application by requiring valid credentials before accessing other features. Figure 6 presents the data prediction form.

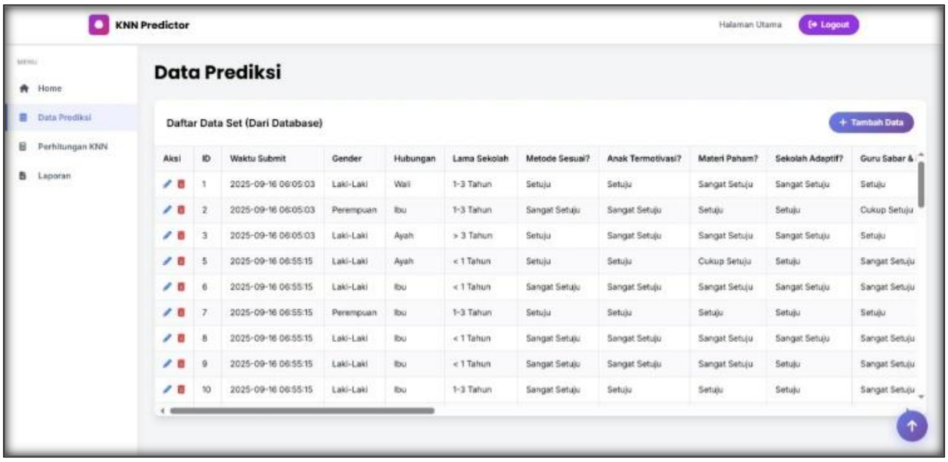


Figure 6. Data prediction form of the system

This form allows users to input parental satisfaction data, including attributes such as learning method, teacher performance, environment, and child development. The data entered here serves as the input for further processing in the K-NN algorithm. Figure 7 presents the menu for K-NN processing.

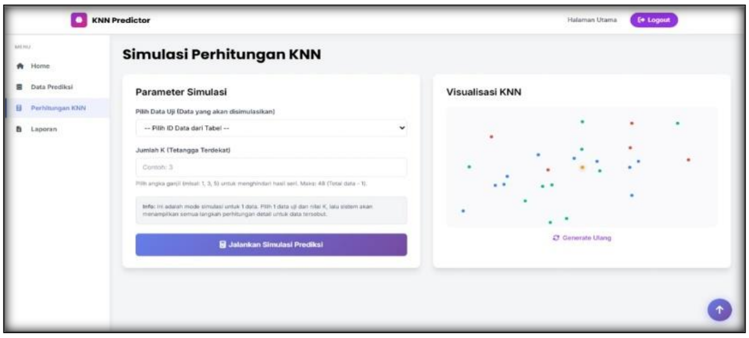


Figure 7. K-NN process menu of the system

The K-NN process menu provides access to the algorithm execution. Through this menu, the system performs distance calculations, identifies the nearest neighbors, and generates classification results. Figure 8 presents the report form of the system.

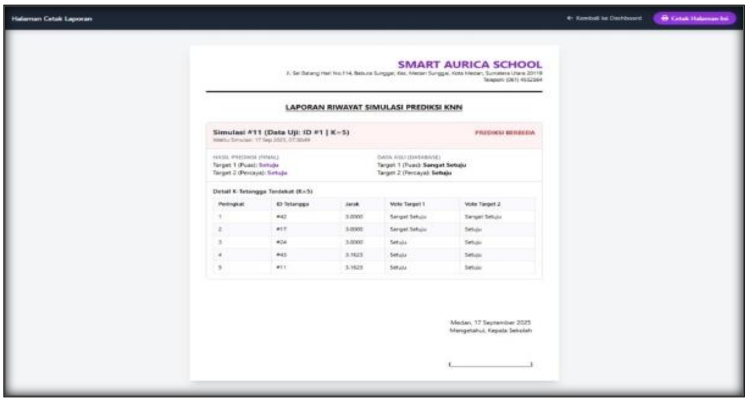


Figure 8. Report form of the system

The report form displays the results of predictions and summarizes the classification outcomes. It enables users to view historical data and prediction outputs in a structured format that can be used for evaluation and decision-making.

Overall, the system interface was designed to be straightforward, focusing on usability and clarity. Each form complements the workflow of the K-NN algorithm, starting from secure login, data entry, algorithm execution, to generating prediction reports. The integration of these interfaces ensures that the system can be used efficiently to support parental satisfaction analysis at Smart Aurica School.

CONCLUSION

This study implemented the K-Nearest Neighbor (K-NN) algorithm to predict parental satisfaction with learning methods at Smart Aurica School. The results showed that the K-NN algorithm was able to classify satisfaction levels accurately based on attributes such as learning method, teacher performance, environment, and child development. Distance calculations using the Euclidean method enabled the identification of the nearest neighbors, and with K = 5, the prediction results demonstrated consistency with the actual satisfaction categories. The findings highlight that most parents expressed satisfaction when teaching quality and child development indicators received high scores, while lower scores on these attributes correlated with neutral or dissatisfied outcomes. Overall, the research confirms that K-NN is an effective and reliable approach for evaluating parental satisfaction, providing a data-driven basis for improving educational quality in inclusive schools.

REFERENCE

Ahluna, F., Tutuarima, C. J., & Santoso, I. (2023). Metode K-Nearest Neighbor Untuk Analisis Sentimen Tentang Penghapusan Ujian Nasional. *Jurnal Ikraith-Informatika*, *7*(2), 1–6.

Alfani W.P.R., A., Rozi, F., & Sukmana, F. (2021). Prediksi Penjualan Produk Unilever Menggunakan Metode K-Nearest Neighbor. *JIPI (Jurnal Ilmiah Penelitian Dan Pembelajaran Informatika)*, *6*(1), 155–160. https://doi.org/10.29100/jipi.v6i1.1910

Azmi, F., Gibran, M. K., Fawwaz, I., Anugrahwaty, R., & Saleh, A. (2025). Intelligent Actuator Control in Smart Agriculture through Machine Learning and Sensor Data Integration. *ZERO: Jurnal Sains, Matematika Dan Terapan*, *9*(1), 150–161. https://doi.org/http://dx.doi.org/10.30829/zero.v9i1.24421

Cindy Kawilda Hasibuan, & Yahfizham Yahfizham. (2023). Analisis Pembelajaran Algoritma Pemrograman. *Jurnal Arjuna : Publikasi Ilmu Pendidikan, Bahasa Dan Matematika*, *1*(5), 274–285. https://doi.org/10.61132/arjuna.v1i5.337

Dewi, S. P., Nurwati, N., & Rahayu, E. (2022). Penerapan Data Mining Untuk Prediksi Penjualan Produk Terlaris Menggunakan Metode K-Nearest Neighbor. *Building of Informatics, Technology and Science (BITS)*, *3*(4), 639–648. https://doi.org/10.47065/bits.v3i4.1408

Fathir Aulia, M., Khalil Gibran, M., Shafwa Aulia Sitorus, N., Nugroho, A., Faiza, N., & Amanda Siregar, H. R. (2025). Transfer Learning Implementation with MobileNetV2 for Cassava Leaf Disease Detection. *Jurnal Teknologi Dan Open Source*, *8*(1), 352–361. https://doi.org/10.36378/jtos.v8i1.4442

Firizkiansah, A., Muhammad, A., & Setiawan, D. (2024). Implementasi Algoritma k-Nearest Neighbor (k-NN) pada Data Ulasan Pelaksanaan Pembelajaran Daring. *JIKOMTI : Jurnal Ilmiah Ilmu Komputer Dan Teknologi Informasi*, *1*(1), 16–23.

Hasugian, A. H., Fakhriza, M., & Lubis, D. R. (2024). Strategi Optimasi Menggunakan Metode Game Theory Dan Markov Chain Terhadap Layanan Marketplace. *Journal of Science and Social Research*, *4307*(August), 1232–1239.

Hayati, N. (2023). Klasifikasi Jenis Bunga Mawar Menggunakan Algoritma K-Nearest Neighbour. *Jurnal Informatika Dan Riset*, *1*(1), 31–37. https://doi.org/10.36308/iris.v1i1.474

Hermiati, R., Asnawati, A., & Kanedi, I. (2021). Pembuatan E-Commerce Pada Raja Komputer

Menggunakan Bahasa Pemrograman Php Dan Database Mysql. *Jurnal Media Infotama*, *17*(1), 54–66. https://doi.org/10.37676/jmi.v17i1.1317

Hidayatullah, R., Abdul Fatah, D., & Yasid, A. (2025). Penerapan Algoritma K-Nearest Neighbor Pada Minat Beli Mobil Bekas Menggunakan Pendekatan Crisp-Dm. *JATI (Jurnal Mahasiswa Teknik Informatika)*, *9*(2), 2210–2217. https://doi.org/10.36040/jati.v9i2.13024

Kristianto, O. (2024). Implementasi Data Mining Pada Instansi Pemerintahan (Systematic Literature Review). *Jurnal Mahasiswa Teknik Informatika*, *8*(3), 3137–3142.

Maulana Husaen, M., & Yuliani, H. (2023). Sytematic Literature Review: Kelayakan Media Pembelajaran Mobile Learning Sebagai Penunjang Pembelajaran MIPA Di Indonesia. *LAMBDA : Jurnal Ilmiah Pendidikan MIPA Dan Aplikasinya*, *3*(2), 78–86. https://doi.org/10.58218/lambda.v3i2.561

Nasution, Y. R., & Raja, A. (2021). PENERAPAN METODE SIMPLE MULTI ATRIBUTE RATING TEHNIQUE DAN ALGORITMA K- NEAREST NEIGHBOR Prodi Ilmu Komputer , Fakultas Sains Dan Teknologi , Universitas Islam Negeri Sumatera Utara. *Journal of Science and Social Research*, *4307*(February), 61–65.

Prasetyawan, D., & Gatra, R. (2022). Algoritma K-Nearest Neighbor untuk Memprediksi Prestasi Mahasiswa Berdasarkan Latar Belakang Pendidikan dan Ekonomi. *JISKA (Jurnal Informatika Sunan Kalijaga)*, *7*(1), 56–67. https://doi.org/10.14421/jiska.2022.7.1.56-67

Supriyanto, J., Alita, D., & Isnain, A. R. (2023). Penerapan Algoritma K-Nearest Neighbor (K-NN) Untuk Analisis Sentimen Publik Terhadap Pembelajaran Daring. *Jurnal Informatika Dan Rekayasa Perangkat Lunak*, *4*(1), 74–80. https://doi.org/10.33365/jatika.v4i1.2468

Widya Utami, N., & Artana, M. (2022). Text Mining Dalam Analisis Sentimen Pembelajaran Daring Di Masa Pandemi Covid 19 Menggunakan Algoritma K-Nearest Neighbor. *Jurnal Informatika Teknologi Dan Sains*, *4*(2), 140–148. https://doi.org/10.51401/jinteks.v4i2.2034