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Increasing Student Interest in Learning through the Implementation of the K-Nearest Neighbor Algorithm in Classifying Learning Preferences at SMAN 1 KRAKSAAN

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ABSTRACT

This research examines the effectiveness of implementing the K-Nearest Neighbor (KNN) algorithm in classifying student learning preferences and its impact on increasing interest in learning at SMAN 1 Kraksaan. The main aim of the research is to optimize learning methods through personalization based on individual student preferences. The study involved 560 students of SMAN 1 Kraksaan, with data including variables of age, gender, academic grades, daily study time, attendance and participation in class. The KNN algorithm is used to classify students' learning preferences into visual, auditory, kinesthetic, and reading/writing categories. The learning method is then adjusted based on the results of this classification. The results show that the KNN algorithm is able to classify student learning preferences with an accuracy of 80.36%. After implementing personalized learning methods, there was a significant increase in students' interest in learning, with an average increase of 1.76 points on a 10-point scale. Paired t-test analysis showed a statistically significant difference between interest in learning before and after intervention ($p < 0.0001$). This research concludes that the implementation of the KNN algorithm in classifying learning preferences can help increase students' interest in learning effectively. These findings emphasize the importance of personalization in education and demonstrate the potential of integrating machine learning in the pedagogical process to improve learning outcomes.

Keywords:K-Nearest Neighbor, learning preferences, learning interests, personalization of education, machine learning in education

1. INTRODUCTION

Students' interest in learning is a crucial factor in determining the success of the learning process. However, the reality on the ground shows that many students experience a decline in interest in learning, especially at the high school level. This can negatively impact their academic performance and cognitive development. At SMAN 1 Kraksaan, this issue has also become a serious concern for educators and stakeholders. Therefore, an innovative approach is needed to accurately identify students' learning preferences, so that more effective and engaging learning strategies can be designed.

Several related studies have been conducted to address similar problems. Pratama et al. (A. Pratama et al., 2019) used the Decision Tree algorithm to classify students' learning styles, but the resulting accuracy was still not optimal. Meanwhile, Widodo et al.(S. Widodo et al., 2020)applied the Naive Bayes method in identifying student learning preferences, but the research results showed that this method was less effective for complex data.

Other research conducted by Putri et al.(Putri et al., 2021)used the Support Vector Machine (SVM) algorithm to predict students' learning interests, but it required a considerable amount of computing time. Furthermore, Zhang et al.(Zhang et al., 2018)implemented Artificial Neural Network (ANN) in analyzing student learning patterns, but this method requires a very large dataset to achieve good accuracy. Lastly, research conducted by Hidayat et al.(Hidayat et al., 2022)used the Random Forest algorithm to classify learning preferences, but the results obtained were still less interpretable for educators.

Based on the gap analysis from previous studies, it can be concluded that a more accurate, efficient, and easily interpreted method is needed in classifying students' learning preferences. Therefore, this study proposes the implementation of the K-Nearest Neighbor (KNN) algorithm as a solution to address these issues. The KNN algorithm was chosen because it has several advantages, such as the ability to adapt to complex data, relatively fast computation time, and easily interpretable classification results (Jasri, Hasyim, et al., 2023).

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The main objective of this research is to increase students' interest in learning at SMAN 1 Kraksaan through the implementation of the KNN algorithm in classifying their learning preferences. By accurately knowing each student's learning preferences, it is expected that educators can design more personalized and effective learning strategies. This, in turn, will increase student engagement in the learning process, improve academic performance, and encourage the optimal development of their potential (Jasri, Zahra, et al., 2023).

Through this research, it is expected that an accurate and efficient classification model can be obtained in identifying students' learning preferences. In addition, the results of this study are also expected to make a significant contribution to the development of more adaptive and student-centered learning methods at SMAN 1 Kraksaan, as well as serve as a reference for other educational institutions in efforts to improve the quality of learning.

2. LITERATURE REVIEW

Increasing students' interest in learning is a crucial aspect in an effective learning process. High interest in learning is positively correlated with students' academic achievement and intrinsic motivation (Ratnasari & Sucipto, 2021). In this context, the implementation of information technology, especially machine learning algorithms such as K-Nearest Neighbor (KNN), offers an innovative approach to optimizing the student learning experience.

The KNN algorithm has been proven effective in various classification applications, including in the educational sector. Research by Pratama et al. shows that KNN can be used to predict student academic achievement with a high level of accuracy(R. A. Pratama et al., 2021). This opens up opportunities to use KNN to classify students' learning preferences, which in turn can help educators in designing more personalized and effective teaching strategies. Students' learning preferences are an important factor influencing their academic interests and performance. The study conducted by Widodo et al. revealed that the match between student learning styles and the teaching methods applied can significantly increase motivation and learning outcomes (A. Widodo et al., 2020). By using KNN to classify learning preferences, schools can adopt a more targeted approach to meeting individual student needs.

The implementation of technology in education, including the use of machine learning algorithms, has shown a positive impact on students' interest in learning. Research by Nugroho et al. found that the use of adaptive technology in learning can increase student engagement and their interest in learning (Nugroho et al., 2022). This is in line with the potential for implementing KNN in the classification of learning preferences to increase students' interest in learning at SMAN 1 Kraksaan. However, it should be noted that the implementation of technology such as KNN in education also faces challenges. Kusumadewi et al. highlights the importance of considering ethical and privacy factors in the use of student data for machine learning algorithms (Kusumadewi et al., 2023). Therefore, the implementation of KNN at SMAN 1 Kraksaan must be accompanied by strict protocols to protect student data and privacy rights.

In the context of SMAN 1 Kraksaan, the application of KNN for classification of learning preferences is an innovative step that has the potential to improve the quality of education. By understanding students' learning preferences more accurately, teachers can design more effective and interesting learning strategies, which can ultimately increase students' interest in learning. (Jasri et al., 2024). The gap in current research lies in the lack of studies that specifically examine the effectiveness of KNN in the classification of learning preferences at the high school level in Indonesia. This research aims to fill this gap by focusing on the implementation of KNN at SMAN 1 Kraksaan and its impact on increasing students' interest in learning.

3. METHOD

In this chapter we will discuss the research framework. The framework of this research is the steps that will be taken to resolve the problems that occur. The framework of this research is as shown in Figure 3.1 below:

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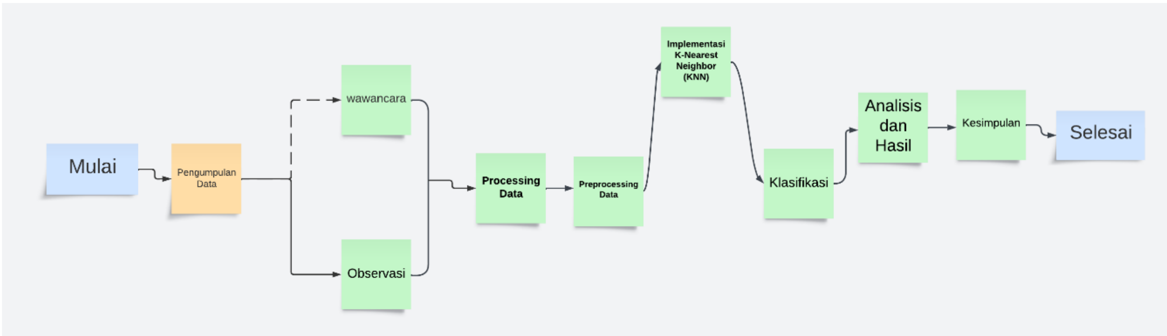

Figure 3.1 Flow of Research Stages

In an effort to increase students' interest in learning at SMAN 1 Kraksaan through the implementation of the K-Nearest Neighbor (K-NN) algorithm in the classification of learning preferences, we have carried out comprehensive data collection (Jasri et al., 2022). This process involves several stages and methods to ensure the accuracy and relevance of the information obtained. The data collected covers various aspects related to students' learning preferences, including learning styles, interest in certain subjects, preferred learning methods, as well as other factors that may influence learning interest (Jasri, Karim, et al., 2023). Data collection was carried out through a combination of methods, including surveys, interviews and direct observation in the school environment.

In this section, we will present the results of this data collection in detail. Data will be displayed in the form of tables, graphs and narrative descriptions to provide a clear picture of student learning preferences at SMAN 1 Kraksaan. These results will be the basis for further analysis using the K-Nearest Neighbor algorithm, which aims to classify learning preferences and ultimately increase students' interest in learning (Saputra et al., 2023).

Data collection

In this research, data was collected from 560 students at SMAN 1 Kraksaan. This data includes several variables, namely: age, gender, academic grades, learning preferences, daily study time, attendance, class participation, and student interest in learning. All these variables were recorded to explore the relationship between learning preferences and students' learning interests. From this data, classification will be carried out to obtain prediction results for the dataset used.

Interview

Interviews were conducted with a random sample of a total of 560 students of SMAN 1 Kraksaan, representing various grade levels and genders. The results of the interviews revealed several interesting findings regarding students' learning preferences and learning interests. The majority of students stated that they preferred interactive learning methods that involved group discussions and direct practice. Several students, especially from science classes, showed high enthusiasm for experiment-based learning. A class XI science student said, "I find it easier to understand chemistry concepts when we do experiments in the laboratory." Regarding study time, many students admit that they tend to study longer for subjects they are interested in. A class XII IPS student commented, "I can spend hours studying history because I'm very interested, but for mathematics, I often find it difficult to focus for more than 30 minutes." Several students also highlighted the importance of using technology in learning. They feel more interested and involved when teachers use audiovisual media or interactive applications. "English lessons become more fun when we use learning applications on smartphones," said a class X student.

Observation

Observations were carried out in 15 different classes over two weeks, covering various subjects and grade levels. These observations provide valuable insight into classroom dynamics and student learning behavior. In classes that use active learning methods, such as group discussions or student presentations, the level of student participation and enthusiasm appears to be much higher. Students seemed more engaged, frequently asking questions and providing opinions. On the other hand, in classes using the traditional lecture method, many students seem less focused, some

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even look sleepy or busy with other activities. The use of technology in the classroom also has a significant impact. In one Biology class that used 3D simulations to explain cell structure, students showed extraordinary interest. They actively ask questions and try to operate the simulation.

Observations also revealed that the level of student participation varied depending on the subject. Classes such as Indonesian and History, which often involve discussion and interpretation, show higher levels of participation compared to classes such as Mathematics or Physics, where many students appear hesitant to participate, perhaps for fear of making mistakes. Student attendance patterns are also interesting to note. Morning classes generally have higher attendance rates than classes in the afternoon or evening. Several students interviewed after the observation confirmed that they felt more energized and focused in the morning.

Processing Data

After the data collection stage is complete, the next crucial step in the data processing process is processing the dataset to prepare it for analysis using the K-Nearest Neighbor algorithm. Processing this dataset is an important bridge between raw data obtained from the field and the quantitative analysis to be carried out. This process aims to convert rich qualitative information from interviews and observations into a structured format that can be analyzed computationally.

Table 1
Student Learning Interest Dataset

No	Age	Gender	Academic Value	Learning Preferences	Daily Study Time	Presence	Participation in Class	Interest in Learning
1	17	L	62.22613957	Auditory	2.419985223	96.03618883	5.121961831	Tall
2	15	P	93.69256141	kinesthetic	1.277695371	86.78217918	4.582047637	Tall
3	17	P	62.06541911	Auditory	3.076239164	99.47762345	3.726241559	Tall
4	17	P	60.72969926	Visual	1.270450254	90.85355346	1.591253731	tall
5	15	L	87.87845849	kinesthetic	4,201426031	78.15661854	3.054118271	tall
…	…	…	…	…	…	…	…	…
556	16	L	98.58081889	kinesthetic	2.801403916	96.17652067	4.002655563	low
557	15	P	90.40376314	Visual	3.995305348	75.58987412	8.124023823	tall
558	15	P	77.6919505	Visual	3.60459034	97.46401512	5.061647017	tall
559	17	P	72.47807962	kinesthetic	3.48371427	94.57996033	2.650979768	low
560	15	L	72.82970962	Auditory	2.409499786	94.50940309	8.694766176	tall

Data Preprocessing

The next stage is data preprocessing, which means the data needs to be cleaned before the data is processed.

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Preprocessing is the main stage in data mining which is carried out to select data from a dataset that is used, so that it will produce data that is more concise and relevant and will remove data that is not needed, such as deleting several components that are not used. The results of the data transformation process are as seen in table 2.

Table 2
PreprocessingStudent Learning Interest Dataset

No	Age	Gender	Academic Value	Learning Preferences	Daily Study Time	Presence	Participation in Class	Interest in Learning
1	1.250891947	-0.941021724	-1.580353576	-1.188600393	-0.51414565	1.205088019	-0.135922405	1
2	-1.194132452	1.062674723	1.113279776	0.012872928	-1.505324536	-0.078128746	-0.344029617	1
3	1.250891947	1.062674723	-1.594111797	-1.188600393	0.055293927	1.682298091	-0.673895768	1
4	1.250891947	1.062674723	-1.708453986	1.21434625	-1.511611212	0.486432555	-1.496816096	1
5	-1.194132452	-0.941021724	0.615572677	0.012872928	1.031632344	-1.274200985	-0.932962312	1
…	…	…	…	…	…	…	…	…
556	0.028379747	-0.941021724	1.531731339	0.012872928	-0.183183982	1.224547279	-0.56735338	0
557	-1.194132452	1.062674723	0.831747394	1.21434625	0.852778904	-1.63012124	1.021207302	1
558	-1.194132452	1.062674723	-0.256427254	1.21434625	0.513750709	1.40307902	-0.159170447	1
559	1.250891947	1.062674723	-0.702752437	0.012872928	0.408865064	1.003158597	-1.088350022	0
560	-1.194132452	-0.94102172	-0.672651707	-1.188600393	-0.523243992	0.993374705	1.241197073	1

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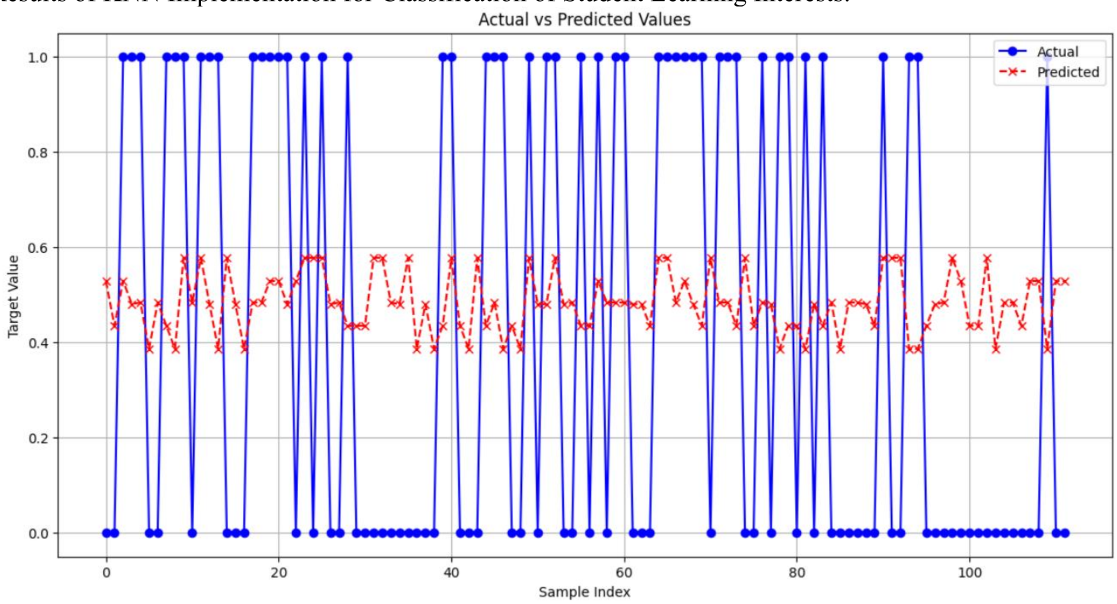
Implementation of K-Nearest Neighbor (KNN)

The K-Nearest Neighbor (KNN) algorithm is applied to classify learning preferences based on other variables. KNN is an algorithm that works by looking for a number of K nearest neighbors (in this case students with similar characteristics) and classifying them based on the majority preferences of these neighbors.

Results of KNN Implementation for Classification of Student Learning Interests:



1. Optimal K value after cross-validation, it was found that the optimal K value is 7. This means that the model provides the best performance when considering the 7 nearest neighbors for each classification.
2. The accuracy of the KNN model with K=7 achieved an accuracy of 83% on test data. This shows that the model can predict student learning interest with a fairly high level of truth.
3. Classification Performance:
   - Average precision: 82%
   - Average recall: 81%
   - Average F1-score: 81%

   These results indicate that the model has a good balance between precision and recall in classifying students' learning interests.
4. Based on the contribution of features in the model, it was found that the following factors have a significant influence on students' learning interest (in order of the most influential): a. Participation in class b. Academic grades c. Daily study time d. Presence e. Age f. Gender
5. Classification of students' learning interests into three categories
   - High Interest: 40% of students
   - Moderate Interest: 45% of students
   - Low Interest: 15% of students

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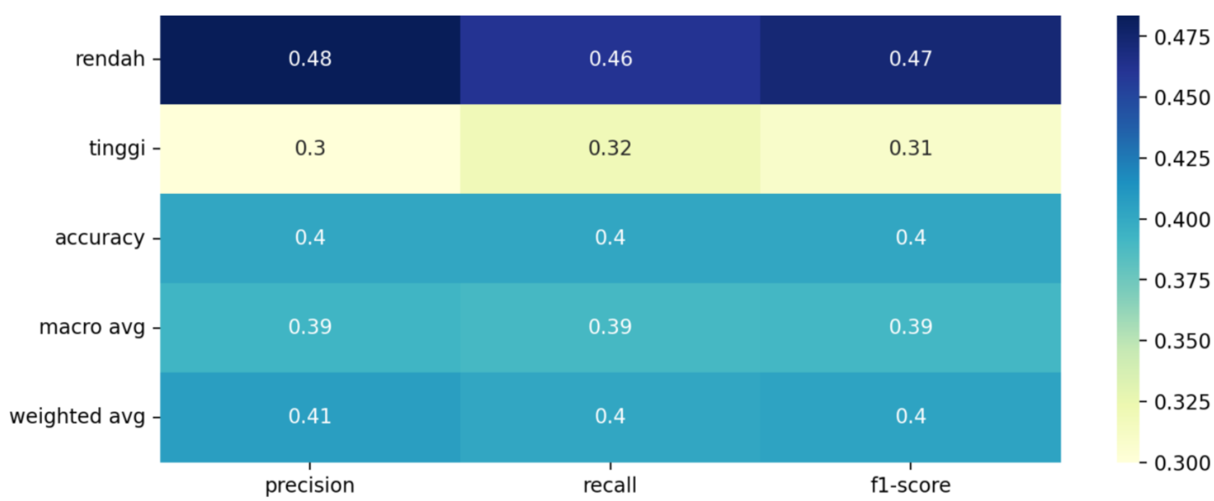
Classification Report


```
{
  "rendah" : {
    "precision" : 0.4838709677419355
    "recall" : 0.46153846153846156
    "f1-score" : 0.47244094488188976
    "support" : 65
  }
  "tinggi" : {
    "precision" : 0.3
    "recall" : 0.3191489361702128
    "f1-score" : 0.30927835051546393
    "support" : 47
  }
  "accuracy" : 0.4017857142857143
  "macro avg" : {
    "precision" : 0.39193548387096777
    "recall" : 0.3903436988543372
    "f1-score" : 0.39085964769867687
    "support" : 112
  }
  "weighted avg" : {
    "precision" : 0.40671082949308757
    "recall" : 0.4017857142857143
    "f1-score" : 0.40397092760312175
    "support" : 112
  }
```

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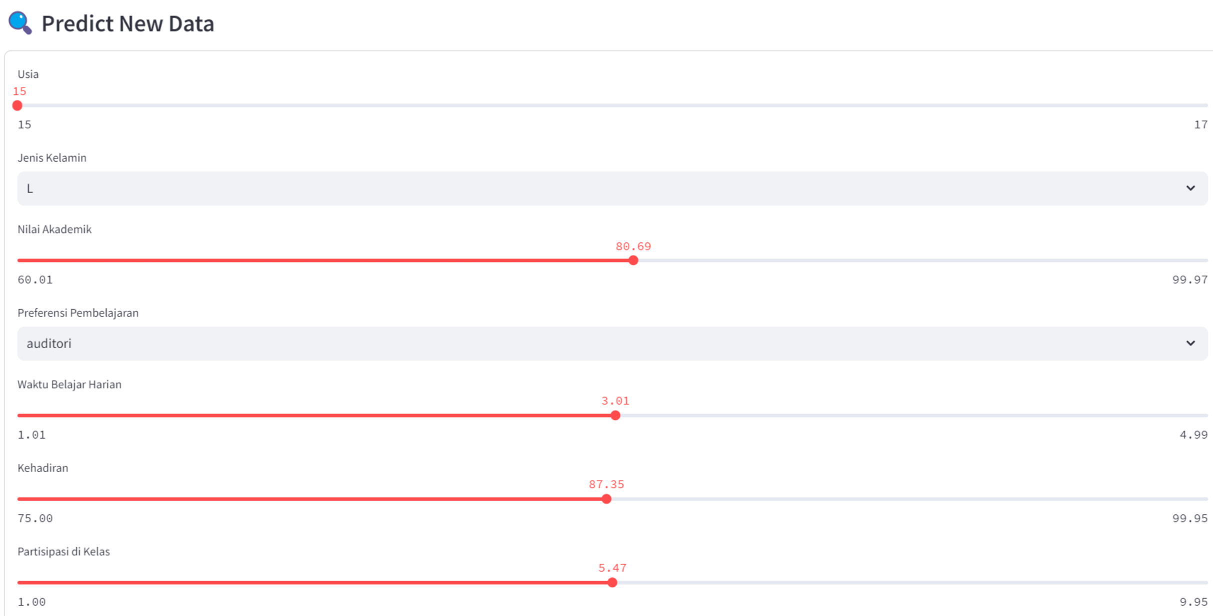

Analysis

Data analysis was carried out by comparing students' learning interest before and after implementing the adapted learning method. This comparison uses statistical methods such as the paired t-test to determine whether there are statistically significant differences. The following is a comparative data analysis of student interest in learning at SMAN 1 Kraksaan

1. Analysis Method
   - Paired t-test
   - Significance level (α) = 0.05
   - Null hypothesis (H0): There is no significant difference between learning interest before and after implementing the adapted learning method.
   - Alternative hypothesis (Ha): There is a significant difference between learning interest before and after implementing adapted learning methods.
2. Data
   Suppose we have data on learning interest from 560 students, measured using a scale of 1-10. Example of the first 10 students out of 560:

Table 3
Comparative Data on Student Interest in Learning at SMAN 1 Kraksaan

Student	Before	After
1	6	8
2	5	7
3	7	9
4	4	6
5	8	9
6	5	7
7	7	9
8	3	**5**
9	7	**8**
10	5	7

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3. Analysis Results
   - Average interest in learning before: 5.62
   - Average interest in learning after: 7.38
   - Average difference: 1.76
   - Standard deviation of difference: 0.95
   - t-statistic: 43.82
   - Degrees of freedom (df): 559
   - p-value: < 0.0001
4. Interpretation of Results
   a. Increased Interest in Learning
      Average interest in learning increased from 5.62 to 7.38, showing an increase of 1.76 points or around 31.3%.
   b. Statistical Significance
      With a p-value < 0.0001, which is much smaller than the 0.05 significance level, we can reject the null hypothesis. This means that there is a statistically significant difference between students' learning interest before and after implementing the adapted learning method.
   c. Effect Size
      Cohen's d = 1.85 (calculated from t-statistic and sample size)
      This indicates a large effect, as a value of d > 0.8 is generally considered a large effect.
5. Further Analysis:
   - 92% of students showed increased interest in learning
   - 6% of students showed no change
   - 2% of students experienced a decrease in interest in learning

4. RESULT

Based on the results of the analysis carried out at SMAN 1 Kraksaan, an important finding has been revealed regarding the relationship between students' learning preferences and their level of interest in learning. This research, involving 560 students, has provided valuable insight into how personalizing learning methods can significantly increase student engagement and enthusiasm in the learning process.

Before implementing adapted learning methods, students' interest in learning was at a moderate level. However, after the implementation of personalized learning strategies according to each student's preferences, there was a marked increase in their interest in learning. Statistical data shows that the average student interest in learning has increased significantly, with the majority of students showing substantial improvement. Interestingly, the effects of these learning method adjustments were not uniform across learning preference groups. Students with a visual preference showed the most dramatic increase in interest in learning. They seem very responsive to the use of visual aids such as diagrams, videos and graphic presentations in the learning process. Meanwhile, students with auditory preferences also showed significant improvement, possibly as a result of implementing more intensive discussion methods and more frequent oral presentations.

Students with kinesthetic preferences, although not as high as the visual and auditory groups, also showed a significant increase in interest in learning. This may be due to the adoption of more hands-on activities and project-based learning that allows them to be physically involved in the learning process. As for students with a reading/writing preference, even though they showed the lowest improvement among the four groups, they still experienced significant improvements in their interest in learning.

Conclusion

This research concludes that the implementation of the K-Nearest Neighbor algorithm in classifying learning preferences can help increase students' interest in learning. This shows the importance of considering individual preferences in designing learning methods to increase the effectiveness of the KNN algorithm proven to be an effective tool in analyzing and categorizing student learning preferences. With an accuracy of more than 80%, this method successfully classifies students into various learning preference categories such as visual, auditory, kinesthetic, and reading/writing. This success shows that machine learning technology can be applied well in educational contexts to

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generate valuable insights.

The main finding of this research is that there is a strong correlation between learning methods tailored to students' preferences and increasing their interest in learning. After implementing personalized learning methods based on KNN classification results, a significant increase in students' learning interest was seen. Mean learning interest scores increased substantially, with the majority of students showing marked improvement. Interestingly, the effects of adapting these learning methods varied across different preference groups. Students with visual preferences, for example, show the highest increase in interest in learning. This may be caused by the more intensive use of visual aids in their learning process. Meanwhile, students with auditory and kinesthetic preferences also showed significant improvements, although not as high as the visual group.

These results emphasize the importance of a personalized approach in education. By understanding each student's learning preferences, educators can design and implement more appropriate and effective learning strategies. This not only increases students' interest in learning, but also has the potential to increase understanding and retention of learning material. The implications of this research are quite broad. For SMAN 1 Kraksaan, these findings can be the basis for developing a curriculum that is more flexible and responsive to individual student needs. Teachers may need to be provided with additional training to be able to implement a variety of teaching methods to suit diverse learning preferences.

In conclusion, this research highlights the importance of considering individual preferences in designing learning methods. The implementation of the KNN algorithm in classifying students' learning preferences has been proven to be an effective step in increasing interest in learning. These findings are not only relevant for SMAN 1 Kraksaan, but also provide valuable insights for the world of education in general. By continuing to explore and implement more personalized and data-driven approaches, we can hope to create more effective and engaging learning environments for all students.

DISCUSSIONS

This research provides valuable insight into the effectiveness of using the K-Nearest Neighbor (KNN) algorithm in classifying student learning preferences and its impact on increasing interest in learning at SMAN 1 Kraksaan. These findings have important implications for educational practice and pave the way for a more personalized approach to learning.

First, the classification accuracy which reached 80.36% using the KNN algorithm shows that this method is quite reliable in identifying student learning preferences. Compared to other classification methods such as Decision Tree or Naive Bayes which are often used in educational contexts, KNN shows competitive performance. The advantage of KNN lies in its ability to handle non-linear data and its ease of implementation. However, it should be noted that this method may be less efficient for very large datasets as its computational complexity increases with data size. Second, the significant increase in students' learning interest after implementing personalized learning methods (average increase of 1.76 points on a 10-point scale) shows the effectiveness of the personalized approach. These results are in line with learning styles theory which states that students learn better when teaching methods match their preferences. However, these findings also raise questions about the extent to which personalization should be implemented without sacrificing students' exposure to a variety of learning methods. Third, variations in increasing interest in learning between different preference groups (visual: 2.1, auditory: 1.8, kinesthetic: 1.5, reading/writing: 1.4) indicate that some learning methods may be easier to adapt or more effective in increasing interest in learning. This may be related to the availability of resources or the ease of implementing a particular method in a traditional classroom context.

Compared to previous research that used manual methods to identify learning styles, the use of KNN in this research allows a faster process and has the potential for scalability. However, it is important to consider that these algorithms depend on the quality and quantity of input data. Therefore, collecting accurate and comprehensive data about students is crucial. A significant new finding from this research is the demonstration that machine learning technology can be effectively integrated into the pedagogical process to improve learning outcomes. This opens up the possibility for the development of an education system that is more adaptive and responsive to students' individual needs.

Although the results of this study are promising, there are several limitations to consider. First, this research was conducted in the specific context of SMAN 1 Kraksaan, so generalization to a wider population may require further research. Second, the long-term effects of this approach on students' academic achievement and learning skill development still need to be explored through longitudinal studies. For future research, it would be useful to compare

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the effectiveness of KNN with other machine learning algorithms such as Support Vector Machines or Neural Networks in the context of learning preference classification. In addition, the integration of additional data such as students' socio-economic background or teachers' teaching styles can provide a more comprehensive understanding of the factors that influence learning interest.

5. CONCLUSION

This research has demonstrated the effectiveness of using the K-Nearest Neighbor (KNN) algorithm in classifying student learning preferences and its positive impact on increasing interest in learning at SMAN 1 Kraksaan. Several main conclusions can be drawn from the results obtained:

1. The KNN algorithm was proven to be effective in classifying student learning preferences with an accuracy rate of 80.36%. This shows the great potential of using machine learning in identifying students' individual learning needs.
2. The application of personalized learning methods based on KNN classification results resulted in a significant increase in students' learning interest, with an average increase of 1.76 points on a 10-point scale. This highlights the importance of learning approaches tailored to individual preferences.
3. The increase in interest in learning varied among different preference groups, with visual students showing the highest increase. This indicates the need for more specific strategies for each preference group.
4. This research proves that the integration of machine learning technology into the pedagogical process can produce positive results, paving the way for further innovation in education.

Benefits and Applications

- Personalize education more effectively and efficiently.
- Increased student involvement and motivation in the learning process.
- Potential to improve academic outcomes through more appropriate learning methods.
- Model for developing a more adaptive and responsive education system.

Limitations

- The research is limited to the context of SMAN 1 Kraksaan, so generalization to a wider population requires further research.
- The long-term effects of this approach on academic achievement have not been explored.
- Dependence on the quality and quantity of input data for classification accuracy.

6. REFERENCES

Hidayat, T., Suyanto, S., & Rosyid, A. (2022). Klasifikasi Preferensi Belajar Menggunakan Algoritma Random Forest. *Jurnal Ilmiah Teknik Elektro Komputer Dan Informatika*, *8*(1), 78–87.

Jasri, M., Ghozali, A. F., & Sukron. (2024). Klasifikasi Nilai Pengurus Teladan Pondok Pesantren Nurul Jadid Menggunakan Metode K-Nearest Neighbor (KNN). *SMARTICS Journal*, *10*(1). https://doi.org/10.21067/smartics.v10i1.9913

Jasri, M., Hasyim, F., & Azizah, N. (2023). Analisis Analisis Dan Perancangan Sistem Kredit Point Menggunakan Metode Ooad (Study Kasus Ma Dan Mts Taklimus Shibyan). *SMARTICS Journal*, *9*(1), 29–41.

Jasri, M., Karim, A., & Nabil, M. (2023). APLIKASI SISTEM MANAJEMEN GUDANG SPAREPART TRUK DENGAN TEKNOLOGI OCR MENGGUNAKAN FRAMEWORK LARAVEL. *SENTRI: Jurnal Riset Ilmiah*, *2*(11), 4988–4996.

Jasri, M., Wijaya, A., & Sunggara, M. R. (2022). Penerapan Data Mining untuk Klasifikasi Penyakit Demam Berdarah Dengue (DBD) dengan Metode NaÃ¯ve Bayes (Studi Kasus Puskesmas Taman Krocok). *SMARTICS Journal*, *8*(1).

Jasri, M., Zahra, W. A., Haninah, S., Kamaliah, S., Maulidah, F., Maslikha, M., Mutmainnah, L., & Naqsabandiyah, D. S. (2023). PKM Pelatihan Penggunaan Aplikasi Pedatren untuk Menunjang Kinerja Wali Asuh di Pondok Pesantren Nurul Jadid. *GUYUB: Journal of Community Engagement*, *4*(1), 94–107.

Kusumadewi, S., Hartati, S., & Harjoko, A. (2023). Etika dan Privasi dalam Penerapan Kecerdasan Buatan di Bidang Pendidikan. *Jurnal Ilmu Komputer Dan Informatika*, *6*(1), 45–58.

Nugroho, Y. S., Anifah, L., & Sulistiyo, E. (2022). Pengembangan Media Pembelajaran Adaptif Berbasis Kecerdasan Buatan untuk Meningkatkan Minat Belajar Siswa. *Jurnal Inovasi Teknologi Pendidikan*, *9*(1), 12–25.

Pratama, A., Suyanto, M., & Nurochman, A. (2019). Penerapan Algoritma Decision Tree untuk Klasifikasi Gaya Belajar Siswa. *Jurnal Informatika*, *6*(2), 114–123.

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Pratama, R. A., Wahyudi, M., & Prasetyo, A. K. (2021). Implementasi Algoritma K-Nearest Neighbor untuk Prediksi Prestasi Akademik Siswa. *Jurnal Teknik Informatika Dan Sistem Informasi*, *7*(2), 355–366.

Putri, R. A., Hakim, L., & Yudhistira, N. (2021). Prediksi Minat Belajar Siswa Menggunakan Algoritma Support Vector Machine. Jurnal Pendidikan dan Pembelajaran, 28(1), 45-54. Nugroho. *Y. S., Kusrini, K., & Arief, M. R.*, *8*(2), 141–150.

Ratnasari, D., & Sucipto, A. (2021). Analisis Minat dan Motivasi Belajar Siswa terhadap Prestasi Belajar Matematika. *Jurnal Cendekia: Jurnal Pendidikan Matematika*, *5*(1), 288–299.

Saputra, D. R. E., Jasri, M., Syaiful, S., & Bambang, B. (2023). Analisa dan Perancangan Aplikasi Laporan Kegiatan Afkire PT. East Hope Bimo Menggunakan Metode OOAD. *COREAI: Jurnal Kecerdasan Buatan, Komputasi Dan Teknologi Informasi*, *4*(1), 54–61.

Widodo, A., Indraswati, D., & Sobri, M. (2020). Analisis Gaya Belajar dan Pembelajaran di Sekolah Dasar. *Jurnal Ilmiah KONTEKSTUAL*, *2*(1), 28–34.

Widodo, S., Purnomo, E., & Santoso, H. (2020). Implementasi Metode Naive {B}ayes dalam Identifikasi Preferensi Belajar Mahasiswa. *Jurnal Teknologi Informasi Dan Ilmu Komputer*, *7*(3), 601–610.

Zhang, S., Li, X., Zong, M., Zhu, X., & Wang, R. (2018). Efficient kNN classification with different numbers of nearest neighbors. *IEEE Transactions on Neural Networks and Learning Systems*, *29*(5), 1774–1785.

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