Al-Khwarizmi: Jurnal Pendidikan Matematika dan Ilmu Pengetahuan Alam
Maret-2024, Vol.12, No.1, hal.15-28
ISSN(P): 2337-7666; ISSN(E):2541-6499
https://ejournal.iainpalopo.ac.id/index.php/al-khwarizmi
DOI: http://dx.doi.org/10.24256/jpmipa.v12i1.3669

Predicting Students' Mathematical Decision Making Using k-Nearest Neighbor Technique

Prediksi Pengambilan Keputusan Matematika menggunakan *k-Nearest Neighbor*

[1]Giyanti, [2]Rina Oktaviyanthi
[1,2]Program Studi Pendidikan Matematika, Universitas Serang Raya
Alamat: [1,2]Jl. Raya Serang – Cilegon Km.5, Serang, Banten, Indonesia
Email: rinaokta@unsera.ac.id

Article History:
Received: 06-03-2023; Received in Revised: 15-03-2024; Accepted: 17-03-2024

Abstract

Mathematical decision-making abilities are mathematical information processing through risk evaluation and investigation of various possibilities and perspectives. However, the evaluation of mathematical decision-making abilities is still limited to high, medium, and a low level based on test scores and is not predictive naturally. The purpose of this study is to identify the parameter k in the k-nearest neighbor technique, which serves as the nearest-neighbor value determining the mathematical decision-making abilities of students to be predicted. The process of data exploration to prediction is employed by the data mining approach with the k-Nearest Neighbor method. A total of 65 first-year students taking Calculus I included as research samples. The research results show that a parameter value of k=15 is better at predicting the closeness of the mathematical decision-making with an accuracy of 93.33%, associated with the excellent category. The parameter value representing the closeness of the decision-making abilities level among students serves as a reference for teacher predictions to categorize students and create diversified teaching materials.

Keywords*: Educational Data Mining; K Parameter Value; Mathematical Decision Making; Nearest Neighbor; Prediction Method.*

Abstrak

Kemampuan pengambilan keputusan matematis merupakan pemrosesan informasi secara matematis melalui evaluasi risiko dan penyelidikan berbagai kemungkinan dan sudut pandang. Namun, evaluasi kemampuan pengambilan keputusan matematis masih terbatas pada level tinggi, sedang dan rendah berdasarkan nilai tes, tidak bersifat prediktif. Penelitian ini bertujuan mengidentifikasi nilai parameter k dengan teknik k-nearest neighbor yang berperan sebagai nilai ketetanggaan terdekat dari kemampuan pengambilan keputusan matematis. Proses eksplorasi data hingga prediksi dilakukan menggunakan pendekatan data mining dengan metode k-Nearest Neighbor. Sebanyak 65 mahasiswa tahun pertama yang mengikuti Kalkulus I sebagai sampel penelitian. Hasil penelitian menunjukkan nilai parameter k=15 yang lebih mampu memprediksi kedekatan tingkat kemampuan pengambilan keputusan matematis dengan akurasi 93,33%, termasuk pada kategori excellent. Nilai parameter tersebut menjadi acuan prediksi pengajar untuk mengkategorikan mahasiswa dan membuat diversifikasi bahan ajar.

Kata Kunci*: Data Mining Pendidikan; Metode Prediksi; Nearest Neighbor; Nilai Parameter K; Pengambilan Keputusan Matematis.*

Introduction

In education, especially mathematics education, mathematical decision-making ability is a new study of collaboration in the fields of education, psychology and artificial intelligence[1]. This research was initiated by the field of psychology related to cognitive process theory and practically dominated by the IT field to design and identify an intelligent system[2]. The cognitive workflow of decision-making in the IT field is in line with the problem-solving work process in mathematics education. This motivation is the background for the assessment of decision-making abilities in the field of education.

In general, it is assumed that decision-making ability is an interaction and processing of information from higher-order thinking processes that involve selecting alternative options, evaluating risks and consequences depending on what one believed, what one desired and what one known[3]. The purpose of developing students' decision-making ability is to provide techniques in making, analyzing and evaluating a decision from the complexity of the problem and as an experience that will be implemented in real life decision making[4]. The search for mathematical decision-making abilities is still limited to high, medium and low levels based on test scores thus other potentials that can optimize the emergence of mathematical decision-making abilities are not visible. Thus, a new method is needed to classify mathematical decision making involving all possible factors.

---

[1] Tim Jülicher, "Education 2.0: Learning Analytics, Educational Data Mining and Co.," in *Big Data in Context: Legal, Social and Technological Insights*, ed. Thomas Hoeren and Barbara Kolany-Raiser, SpringerBriefs in Law (Cham: Springer International Publishing, 2018), 47–53, https://doi.org/10.1007/978-3-319-62461-7_6.

[2] Fabio Bagarello, Irina Basieva, and Andrei Khrennikov, "Quantum Field Inspired Model of Decision Making: Asymptotic Stabilization of Belief State Via Interaction with Surrounding Mental Environment," *Journal of Mathematical Psychology* 82 (February 1, 2018): 159–68, https://doi.org/10.1016/j.jmp.2017.10.002.

[3] Sitanath Biswas, Trilok Pandey, and Sarada Pati, "Achieving Human Level Reasoning and Decision-Making for Autonomous Systems: An Agent's Perspective," *International Journal of Computer Science Issues* 8 (March 1, 2011).

[4] Máté Farkas-Kis, "Decision Making in the Shadow of Mathematical Education," *Journal of Decision Systems*, December 15, 2022, https://www.tandfonline.com/doi/abs/10.1080/12460125.2022.2087417.

The developing process of the prospective mathematical decision-making abilities accomplished through the provision of actions according to the measured ability indicators[5]. It begins with an exploration of the level of mathematical decision-making ability as a basis for consideration in planning actions. However, to this point this level of ability is still limited to the high, moderate and low categories. The category of such ability levels inadequate as a standard reference in giving consideration[6]. It is requisite to make explorations especially prediction matter thus teachers can obtain initial references to determine the steps for developing and optimizing students' abilities at each level in the following years[7]. Therefore, predictive classification is an imperative step that teachers need to take as a reference in planning learning.

Classification is a process of finding a model that describes a concept or data class with the aim of estimating the class of an object whose label is unknown. The model can be in the form of 'if-then' implication rules, decision trees, mathematical formulas or neural networks[8]. The Nearest Neighbor approach is an object classification method based on the closest distance learning data to the object [9].

The *k*-nearest neighbor (*k*-NN) technique is a classification method that aims to find new patterns in the data by connecting existing data patterns with new data. In the classification process, this technique uses neighboring classification as the predictive value of the new test sample[10]. The distance used is the Euclidean Distance, which is the distance that is most commonly used in numerical data. Euclidean Distance is defined as follows:

---

[5] Timo Leuders et al., "Diagnostic Competence of Mathematics Teachers: Unpacking a Complex Construct," in *Diagnostic Competence of Mathematics Teachers: Unpacking a Complex Construct in Teacher Education and Teacher Practice*, ed. Timo Leuders, Kathleen Philipp, and Juliane Leuders, Mathematics Teacher Education (Cham: Springer International Publishing, 2018), 3–31, https://doi.org/10.1007/978-3-319-66327-2_1.

[6] Christina Lau et al., "Perceived Responsibility for Learning, Self-Efficacy, and Sources of Self-Efficacy in Mathematics: A Study of International Baccalaureate Primary Years Programme Students," *Social Psychology of Education* 21, no. 3 (July 1, 2018): 603–20, https://doi.org/10.1007/s11218-018-9431-4.

[7] Zachary Hawes et al., "Relations Between Numerical, Spatial, and Executive Function Skills and Mathematics Achievement: A Latent-Variable Approach," *Cognitive Psychology* 109 (March 1, 2019): 68–90, https://doi.org/10.1016/j.cogpsych.2018.12.002.

[8] A. Kumar, R. Selvam, and K. Kumar, "Review on Prediction Algorithms in Educational Data Mining," *International Journal of Pure and Applied Mathematics* 118 (January 1, 2018): 531–36.

[9] Y. K. Salal, S. Abdullaev, and Mukesh Kumar, "Educational Data Mining : Student Performance Prediction in Academic," 2019, https://www.semanticscholar.org/paper/Educational-Data-Mining-%3A-Student-Performance-in-Salal-Abdullaev/b21fa7245581c3baad2d468cb9d706940de7e010.

[10] Mudasir Ashraf, Majid Zaman, and Muheet Ahmed, "An Intelligent Prediction System for Educational Data Mining Based on Ensemble and Filtering Approaches," *Procedia Computer Science*, International Conference on Computational Intelligence and Data Science, 167 (January 1, 2020): 1471–83, https://doi.org/10.1016/j.procs.2020.03.358.

$$dist(x_1, x_2) = \sqrt{\sum_{i=1}^{n}(x_{1i} - x_{2i})^2}$$

Where:

$dist(x_1, x_2)$ = Distance between objects x_{1i} and x_{2i}

x_{1i} = Testing data

x_{2i} = Training data

n = Data dimension

Several justifications for the utilization of the *k*-NN technique as a choice of classification technique in the field of educational data mining include: (1) its non-parametric category, thereby eliminating the need for assumptions about data distribution and enabling the handling of complex and nonlinear data; (2) its relative simplicity and ease of understanding[11]; (3) the ability of the *k*-NN technique to be extended to multiclass classification without additional modifications; (4) its flexibility and adaptability, allowing the *k*-NN model to be immediately adjusted when new data is added [12].

Classification and prediction using the *k*-NN technique have been widely utilized, particularly in the healthcare sector over the past five years, such as predicting the risk of heart disease based on medical data and patient hereditary factors [13], identifying high-risk behaviors for diabetes [14], and detecting possible symptoms of brain tumors [15]. Furthermore, in the field of education, the use of *k*-NN is also prevalent, such as behavior identification

[11] Maher Ala'raj, Munir Majdalawieh, and Maysam F. Abbod, "Improving Binary Classification Using Filtering Based on K-Nn Proximity Graphs," *Journal of Big Data* 7, no. 1 (March 5, 2020): 15, https://doi.org/10.1186/s40537-020-00297-7.

[12] Juan Isidro González Hidalgo, Silas Garrido T. C. Santos, and Roberto Souto Maior de Barros, "Paired K-NN Learners with Dynamically Adjusted Number of Neighbors for Classification of Drifting Data Streams," *Knowledge and Information Systems* 65, no. 4 (April 1, 2023): 1787–1816, https://doi.org/10.1007/s10115-022-01817-y.

[13] Kumar Kandukuri and A. Sandhya, "Heart Stroke Detection Using KNN Algorithm," *ECS Transactions* 107, no. 1 (April 24, 2022): 18385, https://doi.org/10.1149/10701.18385ecst.

[14] Md. Reshad Reza et al., "Automatic Diabetes and Liver Disease Diagnosis and Prediction Through SVM and KNN Algorithms," in *Emerging Technologies in Data Mining and Information Security*, ed. Aboul Ella Hassanien et al. (Singapore: Springer Nature, 2021), 589–99, https://doi.org/10.1007/978-981-33-4367-2_56.

[15] Soobia Saeed et al., "New Techniques for Efficiently K-NN Algorithm for Brain Tumor Detection," *Multimedia Tools and Applications* 81, no. 13 (May 1, 2022): 18595–616, https://doi.org/10.1007/s11042-022-12271-x.

through voice recognition [16], university enrollment prediction [17], and personalized learning analysis [18].

Despite several studies implementing the k-NN technique, there has been no research focusing on identifying the parameter value k as the nearest neighbor value for the predicted mathematical decision-making abilities. Therefore, this study could provide a methodological contribution, particularly in the field of mathematics education, to evaluate the progress of students' mathematical abilities.

The use of this method is expected to know the distribution of classification and patterns of decision-making ability of the supporting factors. Specifically, the classification distribution of students' mathematical decision-making abilities is expected to support the research objective of predicting student categories based on the closeness of their ability levels.

Method

This study emphasizes the identification of the k parameter value used as the basis for prediction in the *k*-NN technique, where a student has the same mathematical decision-making ability as nearby students up to k. Thus, when new data emerges, it can be predicted which group of mathematical decision-making abilities the data belongs to based on its proximity parameter value (*k* value).

This research method uses quantitative approach and data mining techniques with the *k*-NN classification model. The research steps with the *k*-NN technique in it are as follows:

1. Data preparation
   The activities carried out at the data preparation stage are (a) fixation of the instrument (the mathematical decision-making ability test consists of 7 questions) and (b) data collection.
2. Data processing
   The activities completed in the data processing process are (a) preprocessing aims to check the data whether there is duplication or not, cleaning the data whether it is complete or not, and selecting the data

---

[16] Lomthandazo Matsane, Ashwini Jadhav, and Ritesh Ajoodha, "The Use of Automatic Speech Recognition in Education for Identifying Attitudes of the Speakers," in *2020 IEEE Asia-Pacific Conference on Computer Science and Data Engineering (CSDE)*, 2020, 1–7, https://doi.org/10.1109/CSDE50874.2020.9411528.

[17] Nitesh Kumar Sharma et al., "College Kart and K-NN Algorithm Based Placement Prediction," in *2021 Second International Conference on Electronics and Sustainable Communication Systems (ICESC)*, 2021, 1271–76, https://doi.org/10.1109/ICESC51422.2021.9532987.

[18] Hicham Er-Radi et al., "Personalizing the Learning Experience: An Adaptive Algorithm Model Based on K-NN" (E-Learning and Smart Engineering Systems (ELSES 2023), Atlantis Press, 2024), 50–56, https://doi.org/10.2991/978-94-6463-360-3_7.

according to the needs of the analysis; and (b) data transformation aims to convert data based on categories into ordinal data.

3. Mining and analysis

   The processing data used *k*-NN technique assisted by the RapidMiner software to test the most ideal *k* value (number of nearest neighbors) measuring the distance of the testing data from the training data. Considerations for using the RapidMiner application as a data analysis tool in the research include its user-friendly operational features, availability of visualization tools for easy data pattern comprehension, ability to handle large volumes of data quickly and efficiently, and flexibility to customize the analysis workflow according to research goals and needs.

The subjects participating in this study are based on the scope of the research goal, which is to identify the closest neighborhood values of mathematical decision-making abilities of first-year students at Universitas Serang Raya through the *k*-NN technique. Within the framework of *k*-NN analysis, the role of the sample size is significant as a consideration in making accurate predictions and constructing reliable analytical models. A larger sample size can enhance accuracy and reduce research bias [19]. Given that the number of first-year students at Universitas Serang Raya in the mathematics education and engineering programs studying Calculus is 65 students, the sample for this study is determined to be 65 students, considering the research goal and the Convenience Sampling technique [20].

Results and Discussion

1. Data preparation

The data taken are 65 data on students' mathematical decision-making abilities in the Calculus I course on Limit Functions with indicators as presented in the Table 1.

[19] Wilhelmiina Hämäläinen and Mikko Vinni, "Classifiers for Educational Data Mining," in *Handbook of Educational Data Mining* (CRC Press, 2010).

[20] Paul S Levy and Stanley Lemeshow, *Sampling of Populations: Methods and Applications*, 4th ed. (John Wiley & Sons, 2013), https://www.wiley.com/en-us/Sampling+of+Populations%3A+Methods+and+Applications%2C+4th+Edition-p-9781118627310.

Table 1. Indicators questions of mathematical decision making ability

Ability		Indicators	Questions' Number
Decision-making	B1.1	Finding for alternative solutions of the limit value of a function *f(x)* at point *c*	1
	B1.2	Developing alternative solutions of the limit value of a function *f(x)* at point *c*	2
	B1.3	Analyzing alternative solutions of the limit value of a function *f(x)* at point *c*	3
	B2.1	Selecting the best alternative from solutions of the limit value of a function *f(x)* at point *c*	4
	B2.2	Applying the chosen alternative in solving the limit value of a function *f(x)* at point *c*	5
	B2.3	Evaluating the application of alternative solutions of the limit value of a function *f(x)* at point *c*	6

Table 1. informs the types of questions given to students to assess their mathematical decision-making abilities, particularly in the chapter on Function Limits, corresponding to its indicators [21]. The mathematical decision-making ability instrument consists of 6 questions according to the indicators of decision-making abilities that have been validated and declared conceivable applied to collect data [22].

2. Data processing

A number of 65 data on students' mathematical decision-making abilities have been collected, and then prepared to enter the mining process. From the data collection, the dataset is obtained as attached in the following Table 2. The table describes students' achievement for each decision-making abilities indicator with a total score in the right column.

[21] Jenny M. Dauer, Michelle Lute, and Olivia Straka, "Indicators of Informal and Formal Decision-Making about a Socioscientific Issue," *International Journal of Education in Mathematics, Science and Technology* 5, no. 2 (April 30, 2017): 124–38, https://ijemst.net/index.php/ijemst/article/view/114.

[22] Giyanti Giyanti, Rina Oktaviyanthi, and Usep Sholahudin, "Classyfying Students Decision Making Ability Using K-Nearest Neighbor for Determining Students Supplementary Learning," *BAREKENG: Jurnal Ilmu Matematika Dan Terapan* 17, no. 1 (April 20, 2023): 0559–70, https://doi.org/10.30598/barekengvol17iss1pp0559-0570.

Table 2. Example of research dataset

No	Students	Design/ Hypothesizing			Choice/ Brainstorming			Score	Categories Score
		B1.1	B1.2	B1.3	B2.1	B2.2	B2.3		
1	S1	3	3	5	3	3	5	44	Moderate
2	S2	5	5	10	5	5	10	80	High
3	S3	3	5	5	3	3	5	48	Moderate
4	S4	1	1	5	3	1	5	32	Low
5	S5	3	3	5	5	3	10	58	Moderate

The example dataset in Table 2 illustrates the level of students' mathematical decision-making abilities based on their answers to questions per indicator and the overall score attainment. Furthermore, the data in the form of categories is changed into ordinal form for data standardization. The categories of low, moderate and high mathematical decision-making abilities are then written 1, 2 and 3. Changes in the dataset are shown in the table below.

Table 3. Example of ordinal form dataset

No	Students	Design/ Hypothesizing			Choice/ Brainstorming			Score	Categories Score
		B1.1	B1.2	B1.3	B2.1	B2.2	B2.3		
1	S1	3	3	5	3	3	5	44	2
2	S2	5	5	10	5	5	10	80	3
3	S3	3	5	5	3	3	5	48	2
4	S4	1	1	5	3	1	5	32	1
5	S5	3	3	5	5	3	10	58	2

Table 3. explains the transformation of data in the low, moderate, and high categories into ordinal forms 1, 2, and 3 to facilitate analysis and simplify data pattern recognition.

3. Mining and analysis

The mining and analysis process in this study uses the k-NN technique assisted by the RapidMiner application. There are four k parameters that were experimented in this study those are $k = 5$, $k = 15$, $k = 25$ and $k = 35$. The value of the parameter k which indicates the highest accuracy indicates the number of data neighbors that are closest to the actual data. The mining process using the help of the RapidMiner application starts from inputting the existing dataset into the application. The prepared dataset consist the students' achievement score in problem solving task accordance with indicators of mathematical decision-making abilities.

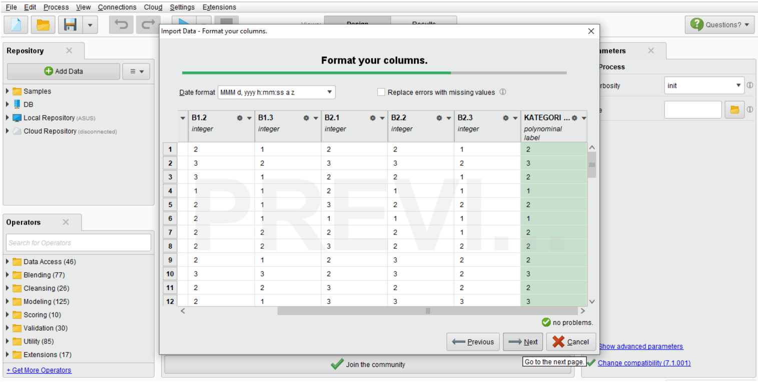

Figure 1. Dataset Input Process

For instance B1.1 finding for alternative solutions of the limit value of a function *f(x)* at point *c*; B1.2 developing alternative solutions of the limit value of a function *f(x)* at point *c*; B1.3 analyzing alternative solutions of the limit value of a function *f(x)* at point *c*; B2.1 selecting the best alternative from solutions of the limit value of a function *f(x)* at point *c*; B2.2 applying the chosen alternative in solving the limit value of a function *f(x)* at point *c*; and B2.3 evaluating the application of alternative solutions of the limit value of a function *f(x)* at point *c*.

Then crosscheck the amount of data and attributes to see whether there is missing data. Furthermore, the analysis process for experiment 1 is attained using the parameter value $k = 15$.

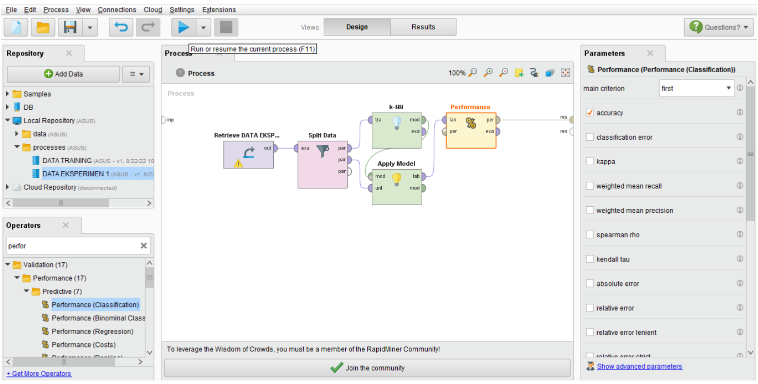

Figure 2. *k*-NN process with RapidMiner for $k = 15$

The results of the model accuracy shown by RapidMiner for the parameter value $k = 15$ are shown in the Figure 3.

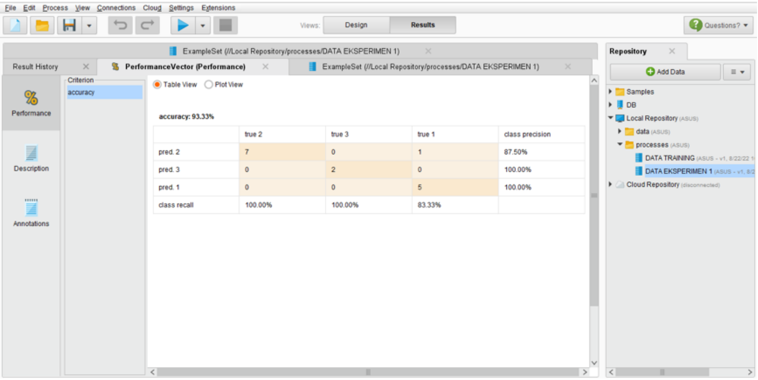

Figure 3. Model accuracy for $k = 15$

The same procedure is applied, the following model performance values are presented for the parameter values $k = 5$, $k = 25$ and $k = 35$.

accuracy: 80.77%

	true 2	true 3	true 1	class precision
pred. 2	10	2	1	76.92%
pred. 3	2	4	0	66.67%
pred. 1	0	0	7	100.00%
class recall	83.33%	66.67%	87.50%	

(a)

accuracy: 46.67%

	true 2	true 3	true 1	class precision
pred. 2	7	2	6	46.67%
pred. 3	0	0	0	0.00%
pred. 1	0	0	0	0.00%
class recall	100.00%	0.00%	0.00%	

(b)

accuracy: 46.67%

	true 2	true 3	true 1	class precision
pred. 2	7	2	6	46.67%
pred. 3	0	0	0	0.00%
pred. 1	0	0	0	0.00%
class recall	100.00%	0.00%	0.00%	

(c)

Figure 4. Model accuracy for $k = 5$ (a), $k = 25$ (b) and $k = 35$ (c)

The results of the classification model's performance accuracy from testing the three k values are summarized in the following Table 4. It contains three columns that describe each k value with the percentage accuracy of the performance model and its accuracy level category. The example for $k = 5$ the calculation shows a performance accuracy of 80,77% and it is at good classification accuracy level.

Table 4 Test Results for k value

k Value	Model Performance Accuracy	Level of Accuracy
5	80,77%	Good classification
15	93,33%	Excellent classification
25	46,67%	Failure
35	46,67%	Failure

Based on Table 4, the accuracy of the classification model performance for the values of $k = 25$ and $k = 35$ is in the diagnosis of failure classification according to the accuracy level [23]. It indicates the number of neighboring data is 25 data and 35 data on the classification unable to provide information on the similarity of the data to each other. Meanwhile, the value of $k = 5$ is at a good level and $k = 15$ is at a very good level. It shows that the number of data closeness as much as 5 and 15 capable of deliver an explanation of the similarity of the data close to the actual fact. As explained by Ramaswami et. al. (2019) a classification level with high accuracy will be able to provide more precise information regarding the similarity of the characteristics of a data [24]. In a review of education, the results of this study adequate to provide a reference for educators in classifying students based on similar characteristics. In alignment with, Tremblay-Wragg (2021) conveys the classification of students' abilities as the basis for teachers to diversify teaching materials with the aim of increasing the potential for understanding the material [25].

Conclusion

Based on data processing and analysis, a parameter value of k = 15 was obtained as the closest value for predicting student categories based on the closeness of their mathematical decision-making abilities level. The model's performance accuracy with a parameter value of k = 15 reached 93.33%, related to the excellent category. This indicates that a student has mathematical decision-making abilities at a similar level and characteristic, as measured by their proximity or closeness to 15 other students. This neighborhood information serves as a reference for educators in grouping

[23] Florin Gorunescu, "Classification Performance Evaluation," in *Data Mining: Concepts, Models and Techniques*, ed. Florin Gorunescu, Intelligent Systems Reference Library (Berlin, Heidelberg: Springer, 2011), 319–30, https://doi.org/10.1007/978-3-642-19721-5_6.

[24] Gomathy Ramaswami et al., "Using Educational Data Mining Techniques to Increase the Prediction Accuracy of Student Academic Performance," *Information and Learning Sciences* 120, no. 7/8 (January 1, 2019): 451–67, https://doi.org/10.1108/ILS-03-2019-0017.

[25] Émilie Tremblay-Wragg et al., "The Use of Diversified Teaching Strategies by Four University Teachers: What Contribution to Their Students' Learning Motivation?," *Teaching in Higher Education* 26, no. 1 (January 2, 2021): 97–114, https://doi.org/10.1080/13562517.2019.1636221.

students based on their abilities and developing strategies for classroom learning planning. Furthermore, the implications of applying the *k*-NN technique to identify the optimal k parameter value to help improve the prediction of students' mathematical decision-making abilities include: (1) educators and universities can explore factors that support students' mathematical decision-making abilities, (2) optimizing the use of classification and prediction techniques in other mathematical abilities, (3) improving learning approaches to optimize mathematical decision-making abilities, and (4) contributing to the development of predictive models not only to understand students' mathematical abilities but also to facilitate appropriate interventions.

Some research recommendations include diversifying classification and prediction methods in the field of mathematics education research by utilizing educational data mining approaches, such as *k*-NN, and exploring predictive models to produce more accurate results for tailored interventions.

Bibliography

Ala'raj, Maher, Munir Majdalawieh, and Maysam F. Abbod. "Improving Binary Classification Using Filtering Based on K-Nn Proximity Graphs." *Journal of Big Data* 7, no. 1 (March 5, 2020): 15. https://doi.org/10.1186/s40537-020-00297-7.

Ashraf, Mudasir, Majid Zaman, and Muheet Ahmed. "An Intelligent Prediction System for Educational Data Mining Based on Ensemble and Filtering Approaches." *Procedia Computer Science*, International Conference on Computational Intelligence and Data Science, 167 (January 1, 2020): 1471–83. https://doi.org/10.1016/j.procs.2020.03.358.

Bagarello, Fabio, Irina Basieva, and Andrei Khrennikov. "Quantum Field Inspired Model of Decision Making: Asymptotic Stabilization of Belief State Via Interaction with Surrounding Mental Environment." *Journal of Mathematical Psychology* 82 (February 1, 2018): 159–68. https://doi.org/10.1016/j.jmp.2017.10.002.

Biswas, Sitanath, Trilok Pandey, and Sarada Pati. "Achieving Human Level Reasoning and Decision-Making for Autonomous Systems: An Agent's Perspective." *International Journal of Computer Science Issues* 8 (March 1, 2011).

Dauer, Jenny M., Michelle Lute, and Olivia Straka. "Indicators of Informal and Formal Decision-Making about a Socioscientific Issue." *International Journal of Education in Mathematics, Science and Technology* 5, no. 2 (April 30, 2017): 124–38. https://ijemst.net/index.php/ijemst/article/view/114.

Er-Radi, Hicham, Souhaib Aammou, Zakaria Tagdimi, and Ikram Amzil. "Personalizing the Learning Experience: An Adaptive Algorithm Model Based on K-NN," 50–56. Atlantis Press, 2024. https://doi.org/10.2991/978-94-6463-360-3_7.

Farkas-Kis, Máté. "Decision Making in the Shadow of Mathematical Education." *Journal of Decision Systems*, December 15, 2022. https://www.tandfonline.com/doi/abs/10.1080/12460125.2022.2087417.

Giyanti, Giyanti, Rina Oktaviyanthi, and Usep Sholahudin. "Classyfying Students Decision Making Ability Using K-Nearest Neighbor for Determining Students Supplementary Learning." *BAREKENG: Jurnal Ilmu Matematika Dan Terapan* 17, no. 1 (April 20, 2023): 0559–70. https://doi.org/10.30598/barekengvol17iss1pp0559-0570.

Gorunescu, Florin. "Classification Performance Evaluation." In *Data Mining: Concepts, Models and Techniques*, edited by Florin Gorunescu, 319–30. Intelligent Systems Reference Library. Berlin, Heidelberg: Springer, 2011. https://doi.org/10.1007/978-3-642-19721-5_6.

Hämäläinen, Wilhelmiina, and Mikko Vinni. "Classifiers for Educational Data Mining." In *Handbook of Educational Data Mining*. CRC Press, 2010.

Hawes, Zachary, Joan Moss, Beverly Caswell, Jisoo Seo, and Daniel Ansari. "Relations Between Numerical, Spatial, and Executive Function Skills and Mathematics Achievement: A Latent-Variable Approach." *Cognitive Psychology* 109 (March 1, 2019): 68–90. https://doi.org/10.1016/j.cogpsych.2018.12.002.

Hidalgo, Juan Isidro González, Silas Garrido T. C. Santos, and Roberto Souto Maior de Barros. "Paired K-NN Learners with Dynamically Adjusted Number of Neighbors for Classification of Drifting Data Streams." *Knowledge and Information Systems* 65, no. 4 (April 1, 2023): 1787–1816. https://doi.org/10.1007/s10115-022-01817-y.

Jülicher, Tim. "Education 2.0: Learning Analytics, Educational Data Mining and Co." In *Big Data in Context: Legal, Social and Technological Insights*, edited by Thomas Hoeren and Barbara Kolany-Raiser, 47–53. SpringerBriefs in Law. Cham: Springer International Publishing, 2018. https://doi.org/10.1007/978-3-319-62461-7_6.

Kandukuri, Kumar, and A. Sandhya. "Heart Stroke Detection Using KNN Algorithm." *ECS Transactions* 107, no. 1 (April 24, 2022): 18385. https://doi.org/10.1149/10701.18385ecst.

Kumar, A., R. Selvam, and K. Kumar. "Review on Prediction Algorithms in Educational Data Mining." *International Journal of Pure and Applied Mathematics* 118 (January 1, 2018): 531–36.

Lau, Christina, Anastasia Kitsantas, Angela D. Miller, and Ellen B. Drogin Rodgers. "Perceived Responsibility for Learning, Self-Efficacy, and Sources of Self-Efficacy in Mathematics: A Study of International Baccalaureate Primary Years Programme Students." *Social Psychology of Education* 21, no. 3 (July 1, 2018): 603–20. https://doi.org/10.1007/s11218-018-9431-4.

Leuders, Timo, Tobias Dörfler, Juliane Leuders, and Kathleen Philipp. "Diagnostic Competence of Mathematics Teachers: Unpacking a Complex Construct." In *Diagnostic Competence of Mathematics Teachers: Unpacking a Complex Construct in Teacher Education and Teacher Practice*, edited by Timo Leuders, Kathleen Philipp, and Juliane Leuders, 3–31. Mathematics Teacher Education. Cham: Springer International Publishing, 2018. https://doi.org/10.1007/978-3-319-66327-2_1.

Levy, Paul S, and Stanley Lemeshow. *Sampling of Populations: Methods and Applications*. 4th ed. John Wiley & Sons, 2013. https://www.wiley.com/en-us/Sampling+of+Populations%3A+Methods+and+Applications%2C+4th+Edition-p-9781118627310.

Matsane, Lomthandazo, Ashwini Jadhav, and Ritesh Ajoodha. "The Use of Automatic Speech Recognition in Education for Identifying Attitudes of the Speakers." In *2020 IEEE Asia-Pacific Conference on Computer Science and Data Engineering (CSDE)*, 1–7, 2020. https://doi.org/10.1109/CSDE50874.2020.9411528.

Ramaswami, Gomathy, Teo Susnjak, Anuradha Mathrani, James Lim, and Pablo Garcia. "Using Educational Data Mining Techniques to Increase the Prediction Accuracy of Student Academic Performance." *Information and Learning Sciences* 120, no. 7/8 (January 1, 2019): 451–67. https://doi.org/10.1108/ILS-03-2019-0017.

Reza, Md. Reshad, Gahangir Hossain, Ayush Goyal, Sanju Tiwari, Anurag Tripathi, Anupama Bhan, and Pritam Dash. "Automatic Diabetes and Liver Disease Diagnosis and Prediction Through SVM and KNN Algorithms." In *Emerging Technologies in Data Mining and Information Security*, edited by Aboul Ella Hassanien, Siddhartha Bhattacharyya, Satyajit Chakrabati, Abhishek Bhattacharya, and Soumi Dutta, 589–99. Singapore: Springer Nature, 2021. https://doi.org/10.1007/978-981-33-4367-2_56.

Saeed, Soobia, Afnizanfaizal Abdullah, N. Z. Jhanjhi, Mehmood Naqvi, and Anand Nayyar. "New Techniques for Efficiently K-NN Algorithm for Brain Tumor Detection." *Multimedia Tools and Applications* 81, no. 13 (May 1, 2022): 18595–616. https://doi.org/10.1007/s11042-022-12271-x.

Salal, Y. K., S. Abdullaev, and Mukesh Kumar. "Educational Data Mining : Student Performance Prediction in Academic," 2019. https://www.semanticscholar.org/paper/Educational-Data-Mining-%3A-Student-Performance-in-Salal-Abdullaev/b21fa7245581c3baad2d468cb9d706940de7e010.

Sharma, Nitesh Kumar, Aniket Kumar Singh, Shubham Salvi, and Shraddha S. More. "College Kart and K-NN Algorithm Based Placement Prediction." In *2021 Second International Conference on Electronics and Sustainable Communication Systems (ICESC)*, 1271–76, 2021. https://doi.org/10.1109/ICESC51422.2021.9532987.

Tremblay-Wragg, Émilie, Carole Raby, Louise Ménard, and Isabelle Plante. "The Use of Diversified Teaching Strategies by Four University Teachers: What Contribution to Their Students' Learning Motivation?" *Teaching in Higher Education* 26, no. 1 (January 2, 2021): 97–114. https://doi.org/10.1080/13562517.2019.1636221.