Journal of Informatics Management and Information Technology
ISSN 2774-4744 (Media Online)
Vol 6, No 1, January 2026 | Hal 116-127
DOI: 10.47065/jimat.v6i1.961
https://hostjournals.com/jimat

Classification of Student Graduation using The Rough Set Method at Public Elementary School

Sigit Prabowo*, Muhammad Iqbal

Master Program, Master of Information Technology, University of Pembangunan Panca Budi, Medan, Indonesia
Email: [1,*]prabowosigit1@gmail.com, [2]muhammadiqbal@gmail.com
Corresponding Author Email: prabowosigit1@gmail.com

Abstract−Education is an important process in developing individual potential, including intellectual, emotional, social, and moral aspects. The student graduation rate is the main indicator of educational success at the elementary school level. However, Vocational High School Putra Anda Binjai faces challenges in determining student graduation due to inaccuracy in classification, which can impact the quality of education. This study implements the Rough Set method as an approach in classifying student graduation based on academic factors such as grades, attendance, behavior, and character. The Rough Set method is able to handle inaccurate and inconsistent data and find hidden patterns that can improve classification accuracy. This study uses student academic datasets to build a classification model that will be evaluated using accuracy and effectiveness measures. This study contributes to improving academic decision making and the quality of education in elementary schools through more accurate graduation classification.

Keywords: Classification; Student Graduation; Rough Set; Academic Data

1. INTRODUCTION

Education is a fundamental pillar in the development of human resources and plays a vital role in shaping individuals who are knowledgeable, skilled, and possess good character. At the elementary school level, education serves as the foundation for students' cognitive, affective, and psychomotor development. The success of education at this level is commonly reflected in students' graduation outcomes, which indicate whether learners have achieved the required academic competencies and character standards determined by educational institutions [1],[2],[3]. Student graduation is a critical indicator of educational quality and effectiveness [4],[5]. However, determining student graduation is not a simple task, as it involves multiple assessment criteria. Graduation decisions are not solely based on academic performance, but also influenced by non-academic factors such as attendance, behavior, and moral character. These factors collectively represent the holistic development of students. In practice, many elementary schools still rely on conventional evaluation methods, such as calculating average scores and subjective judgments from educators. Such approaches may lead to inaccuracies, inconsistencies, and bias, especially when dealing with large volumes of student data [6].

Along with the rapid advancement of information technology, data-driven decision-making has become increasingly important in the education sector. Data mining is one of the techniques that can be utilized to process large datasets and extract meaningful patterns to support decision-making [7],[8],. In educational contexts, data mining has been widely applied for various purposes, including predicting student performance, analyzing learning behavior, clustering students based on academic ability, and classifying graduation outcomes. By applying data mining techniques, educational institutions can make more objective, accurate, and transparent decisions.

Classification is one of the main tasks in data mining that aims to assign data objects into predefined categories based on certain attributes. In the context of student graduation, classification techniques can be used to determine whether a student passes or fails based on academic and non-academic attributes. Several classification algorithms have been commonly used in educational data mining, such as Decision Tree, Naïve Bayes, K-Nearest Neighbor, and Support Vector Machine. However, many of these methods require large datasets, probabilistic assumptions, or complex parameter tuning, which may not always be suitable for educational data that often contains uncertainty and inconsistency [9],[10],[11].

One classification method that is well-suited for handling uncertain and incomplete data is the Rough Set method [12]. The Rough Set theory was introduced as a mathematical approach to deal with vagueness and ambiguity in data analysis without requiring additional information such as probability distributions or membership functions. The main advantage of the Rough Set method lies in its ability to perform attribute reduction and generate decision rules that are easy to interpret [11],[13],[14]. Through the reduction process, irrelevant attributes can be eliminated while preserving essential information, resulting in a simpler yet effective decision model.

Previous studies have demonstrated that the Rough Set method is effective in various domains, including education. Research has shown that Rough Set can be used to predict learning outcomes, analyze student performance, and identify key factors influencing academic success. Compared to other classification methods, Rough Set provides transparent and deterministic decision rules, which are particularly beneficial in educational settings where interpretability and fairness are essential [15]. Despite these advantages, the application of the Rough Set method in elementary school graduation classification is still relatively limited, creating opportunities for further exploration [16].

Public Elementary School 064983 faces challenges in determining student graduation accurately due to the increasing number of students and the complexity of assessment data. Graduation decisions must consider not only academic achievement but also attendance records, behavior, and moral character. Without a systematic and data-driven approach, the graduation decision-making process may become less objective and inconsistent. Therefore, it is necessary

ISSN 2774-4744 (Media Online)
Vol 6, No 1, January 2026 | Hal 116-127
DOI: 10.47065/jimat.v6i1.961
https://hostjournals.com/jimat

to implement a classification method that can handle multiple attributes and provide clear decision rules to support school administrators and educators [17],[18],[19].

Previous studies in educational data mining have predominantly focused on predicting student academic performance using classification methods such as Decision Tree, Naïve Bayes, K-Nearest Neighbor, and Support Vector Machine, which often operate as black-box models and do not provide interpretable decision rules for educators. In addition, most of these studies emphasize academic scores without systematically integrating behavioral and moral aspects into the classification process. Although the Rough Set method has been applied in educational contexts, its use has largely been limited to predicting learning outcomes rather than classifying student graduation at the elementary school level. Furthermore, there is limited evidence regarding which attributes are truly essential in determining graduation decisions, particularly whether attendance plays a significant role after attribute reduction. This indicates a clear research gap in applying the Rough Set method for transparent and attribute-efficient student graduation classification that integrates both academic and character dimensions.

Based on these considerations, this study aims to implement the Rough Set method to classify student graduation at Public Elementary School 064983 using academic and non-academic data. The attributes used in this study include academic average scores, attendance, behavior, and moral character. The expected outcome of this research is a classification model and a set of decision rules that can accurately determine student graduation status. Furthermore, this study is expected to contribute to the development of educational data mining applications, particularly at the elementary school level, by providing an alternative decision-support approach that is objective, transparent, and easy to interpret.

2. RESEARCH METHODOLOGY

2.1 Research Stages

This research was conducted using quantitative research methods with a data mining (classification) approach through several stages that were systematically arranged to ensure that the research process was structured and the results obtained were in accordance with the research objectives. The research stages began with problem identification and ended with the evaluation of student graduation classification results. In general, the research flow can be seen in the following diagram is shown in Figure 1:

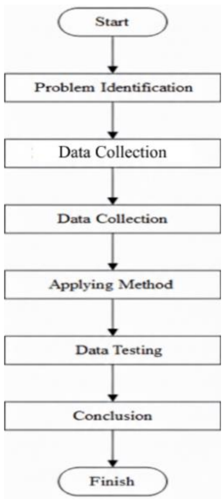


Figure 1. Research Stage Diagram

The research stages outlined in this flowchart describe the research process that will be undertaken as well as the research as a whole. The stages can be described as follows:

a. Problem Identification
   Problem identification is the process of finding, recognizing, and formulating a problem that needs to be solved.
b. Data Collection
   Collecting data from sources such as student academic data, including academic grades, attendance, and behavior, requires checking for completeness before entering the preprocessing stage.
c. Data Processing
   Collecting, cleaning, analyzing, and displaying data so that it is easier to use and interpret is known as data processing.
d. Applying Methods
   In this study, the author uses a classification data mining technique with the Rough Set algorithm to find solutions to a research problem.
e. Testing Data
   At this stage, the results of the analysis from the application of the Rough Set algorithm are presented. These results provide an overview of the main factors that influence student graduation classification.

Journal of Informatics Management and Information Technology
ISSN 2774-4744 (Media Online)
Vol 6, No 1, January 2026 | Hal 116-127
DOI: 10.47065/jimat.v6i1.961
https://hostjournals.com/jimat

f. Conclusion
This study will produce rules in the conclusions obtained from the classification of student graduation.

2.2 Problem Solving Methods

The problem-solving method in this study uses the Rough Set algorithm, which is a classification method in data mining for handling uncertain and incomplete data. The Rough Set algorithm used in the calculation process in this study can be explained as follows Figure 2:

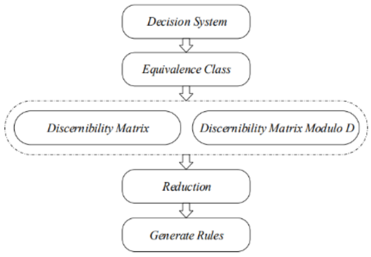


Figure 2. Rough Set Algorithm Flowchart

a. Decision System: The initial stage of the decision system consists of a collection of data containing condition attributes and decision attributes (classes). This data is used for classification and analysis.
b. Equivalence Class: A group of data that has the same condition attribute values. The purpose of this stage is to collect objects that have comparable characteristics.
c. Discernibility Matrix: Determines pairs of objects that can be distinguished based on condition attributes. This matrix helps find attributes that are relevant in distinguishing data. The Modulo D matrix is modified by considering decision attributes (D), so that only attributes relevant to a particular class are considered.
d. Discernibility Matrix Modulo D: The Discernibility Matrix is modified by considering the decision attribute (D), so that only attributes related to a particular class are taken into consideration.
e. Reduction: This process simplifies attributes without losing important information. Unimportant attributes are eliminated, so that only the main attributes are used.
f. Generate Rules: Classification rules are created from the reduction results. Using these rules, we can see the relationship between condition attributes and decisions. This can then be used for prediction or classification of new data.

One important component of the research is the data collection process. The data collection methods used in this study consist of the following procedures:

a. Observation
This research was conducted through direct observation at State Elementary School 064983, with a focus on monitoring and storing academic data related to the number of elementary school graduates in the previous period. This observation was conducted to explore the practices of collecting, compiling, and managing academic data relevant to student graduation classification using the Rough Set method based on academic data.
b. Academic Data
Information related to student academic performance, which typically includes academic grades, attendance, behavior, and character.

3. RESULTS AND DISCUSSION

3.1 Data Analysis

After the students' academic data has been collected, the data analysis stage is carried out. In the context of this study, the information analyzed comes from the students' academic data. The researcher selected important attributes, such as academic grades, attendance, behavior, and character, to be used in the Rough Set model. After the data was collected in Table 1, it was processed using software such as Rosetta to build the Rough Set model used in the data processing.

Table 1. Dataset on Graduation of Students at Public Elementary School 064983

Responden	Nilai											
	Agama	PKN	B.Indo	Matematika	IPA	IPS	Seni Budaya	PJOK	Mulok	Kehadiran	Perilaku	Budi Pekerti
R1	80	85	82	83	82	86	78	81	76	100	90	90
R2	82.1	78.7	75.7	74.7	78.3	79	80.4	81.2	76.8	100	90	90
R3	81.6	76.7	74.7	75.2	79.3	79.5	79.4	80.2	77.8	100	90	90
R4	72.1	72	71.2	70	70.4	71.2	72	71	70	80	60	65
R5	83.1	77.7	76.2	75.2	70.4	76.5	76.9	81.2	76.3	100	75	75
R6	82.1	76.7	77.2	75.7	76.3	77,5	77.9	81.7	76.3	100	90	90
R7	85.1	73.8	75.6	78.1	77.3	76	74.2	81.1	77.8	100	90	90

ISSN 2774-4744 (Media Online)
Vol 6, No 1, January 2026 | Hal 116-127
DOI: 10.47065/jimat.v6i1.961
https://hostjournals.com/jimat

Responden	Agama	PKN	B.Indo	Matematika	IPA	IPS	Nilai Seni Budaya	PJOK	Mulok	Kehadiran	Perilaku	Budi Pekerti
R8	80.1	75.2	78.2	75.4	71.6	75.2	80.1	72.2	78.2	100	90	90
R9	79.2	76.3	77.8	79.4	78.1	76.9	75.5	77.2	78.6	100	90	90
R10	77.7	78.2	78.5	77	78.1	79.6	86.4	76.6	81.8	100	90	90
R11	86.3	85.4	86.2	86.5	85.2	85.9	84.9	85.4	81.1	100	80	85
R12	77.9	78.1	76.6	75.8	77	75.2	74.9	76.6	77.2	100	90	90
R13	76.7	74.8	74.4	76	79.1	78.8	77	77.4	74	100	90	90
R14	81.5	81.2	81.9	79.4	82.3	83.1	84.5	81.5	84.1	100	90	90
R15	85.9	88.2	84.4	85.4	82.5	85.1	86.6	87.1	84	100	90	90
R16	84.4	86.7	83.5	77.8	82.5	82.5	84.4	84.8	74.8	100	90	90
R17	81.6	81.5	79.7	76.5	77.8	80.9	81.6	80.3	75.8	80	65	65
R18	79.4	76.2	80.2	76.4	76.3	78.1	78.7	78.3	79.2	100	90	90
…	…	…	…	…	…	…	…	…	…	…	…	…
R108	77.3	83.7	76.9	79.4	81.2	78.6	77.7	75.4	75.5	100	90	90

3.2 Results of Rough Set Method Application

This study produced a classification model for elementary school student graduation by applying the Rough Set method based on academic data. The results obtained were the output of a series of data analysis processes that included initial data review, transformation of numerical data into categorical form, formation of a decision system, and extraction of decision rules using Rosetta software. Each stage was carried out sequentially to ensure the validity and consistency of the classification results.

3.2.1. Description and Evaluation of Research Data

The analyzed dataset consists of 108 data points from students at Public Elementary School 064983, collected during the period from 2021 to 2024. The data includes academic and non-academic attributes used as the basis for determining student graduation. Academic attributes are represented by average learning scores, while non-academic attributes include attendance, behavior, and character. An initial evaluation of the data shows that most students are in the moderate to high academic category with relatively consistent attendance rates. However, a small number of students were found to have low academic scores and poor behavior. The initial dataset used in this study is presented in Table 2, containing students' academic performance, attendance, behavior, moral character, and graduation decisions.

Table 2. Initial Data

Respondents	Year	Academic	Attendance	Behavior	Moral Character	Decision
R1	2021	81,44	100	90	90	pass
R2	2021	78,54	100	90	90	pass
R3	2021	78,27	100	90	90	pass
R4	2021	71,10	80	60	65	Fail
R5	2021	77,06	100	75	75	pass
R6	2021	69,32	100	90	90	pass
R7	2021	77,67	100	90	90	pass
R8	2021	76,24	100	90	90	pass
R9	2021	77,67	100	90	90	pass
R10	2021	79,32	100	90	90	pass
R11	2021	85,21	100	80	85	pass
R12	2021	76,59	100	90	90	pass
R13	2021	76,02	100	90	90	pass
R16	2021	82,38	100	90	90	pass
R17	2021	79,52	80	65	65	pass
R18	2021	78,09	100	90	90	pass
R19	2021	77,81	100	90	90	pass
R20	2021	83,49	100	90	90	pass
R21	2021	76,91	100	90	90	pass
R22	2021	79,32	100	90	90	pass
R23	2021	85,21	100	90	90	pass
R24	2021	77,68	100	90	90	pass
R25	2021	78,78	100	90	90	pass
R26	2021	77,01	100	90	90	pass
R27	2021	78,51	100	90	90	pass
R28	2021	78,41	100	90	90	pass
R29	2021	82,17	100	90	90	pass
R30	2021	85,47	100	90	90	pass
R31	2021	82,18	100	90	90	pass

ISSN 2774-4744 (Media Online)
Vol 6, No 1, January 2026 | Hal 116-127
DOI: 10.47065/jimat.v6i1.961
https://hostjournals.com/jimat

Respondents	Year	Academic	Attendance	Behavior	Moral Character	Decision
R32	2022	82,13	100	90	90	pass
R33	2022	81,36	100	90	90	pass
R34	2022	79,49	100	90	90	pass
R35	2022	80,96	100	90	90	pass
R36	2022	78,00	100	90	90	pass
R37	2022	79,94	100	90	90	pass
R38	2022	79,11	100	90	90	pass
R39	2022	78,10	100	90	90	pass
R40	2022	78,03	100	90	90	pass
R41	2022	78,82	100	90	90	pass
R42	2022	81,69	100	90	90	pass
R43	2022	77,73	100	90	90	pass
R44	2022	79,56	100	90	90	pass
R45	2022	81,70	100	90	90	pass
R46	2022	76,27	100	90	90	pass
R47	2022	76,59	100	90	90	pass
R48	2022	76,47	100	90	90	pass
R49	2022	82,17	100	90	90	pass
R50	2022	85,47	100	90	90	pass
R51	2022	82,17	100	90	90	pass
R52	2022	85,47	100	90	90	pass
R53	2022	83,08	100	90	90	pass
R54	2022	81,11	100	90	90	pass
R55	2022	78,82	100	90	90	pass
R56	2022	81,69	100	90	90	pass
R57	2022	77,73	100	90	90	pass
R58	2022	79,56	100	90	90	pass
R59	2022	81,70	100	90	90	pass
R60	2023	75,32	100	90	90	pass
R61	2023	83,22	70	50	60	pass
R62	2023	78,54	100	90	90	pass
R63	2023	78,27	100	90	90	pass
R64	2023	71,10	85	78	77	Fail
R65	2023	77,06	90	60	70	pass
R66	2023	69,32	100	90	90	pass
R67	2023	77,88	100	90	90	pass
R68	2023	77,10	100	90	90	pass
R69	2023	80,27	100	90	90	pass
R70	2023	76,16	100	90	90	pass
R71	2023	76,66	100	90	90	pass
R72	2023	75,71	100	90	90	pass
R73	2023	76,04	100	90	90	pass
R74	2023	75,43	100	90	90	pass
R75	2023	77,54	100	90	90	pass
R76	2023	76,49	100	90	90	pass
R77	2023	78,27	100	90	90	pass
R78	2023	77,67	100	90	90	pass
R79	2023	76,24	100	90	90	pass
R80	2023	77,67	100	90	90	pass
R81	2024	79,52	100	90	90	pass
R82	2024	78,09	100	90	90	pass
R83	2024	77,81	75	80	80	pass
R84	2024	83,49	100	90	90	pass
R85	2024	76,91	100	90	90	pass
R86	2024	79,32	100	90	90	pass
R87	2024	85,21	100	90	90	pass
R88	2024	76,59	100	90	90	pass
R89	2024	76,47	100	90	90	pass
R90	2024	82,17	100	90	90	pass
R91	2024	85,47	100	90	90	pass
R92	2024	83,08	100	90	90	pass

ISSN 2774-4744 (Media Online)
Vol 6, No 1, January 2026 | Hal 116-127
DOI: 10.47065/jimat.v6i1.961
https://hostjournals.com/jimat

Respondents	Year	Academic	Attendance	Behavior	Moral Character	Decision
R93	2024	81,11	100	90	90	pass
R94	2024	71,10	100	75	75	Fail
R95	2024	75,50	100	90	90	pass
R96	2024	78,46	100	90	90	pass
R97	2024	78,03	100	90	90	pass
R98	2024	78,82	100	90	90	pass
R99	2024	81,69	100	90	90	pass
R100	2024	77,73	100	90	90	pass
R101	2024	79,56	100	90	90	pass
R102	2024	81,70	100	90	90	pass
R103	2024	76,27	100	90	90	pass
R104	2024	77,68	100	90	90	pass
R105	2024	78,78	90	90	90	pass
R106	2024	77,01	100	90	90	pass
R107	2024	78,51	100	90	90	pass
R108	2024	78,41	100	90	90	pass

3.2.2. Data Transformation through Discretization

The Rough Set method requires categorical data, so numerical data must be transformed through a discretization process. Discretization is performed to simplify data representation without losing essential information that affects graduation decisions. Academic attributes are grouped into low, medium, and high categories. Attendance attributes are divided based on student attendance percentages, while behavior and character attributes are classified into poor, fair, and good categories. The determination of category boundaries is based on school evaluation standards and data distribution characteristics. Before student academic data is used in the classification process using the Rough Set method in Rosetta software, the numerical data is first converted into categorical form (discretization). The converted data includes academic average scores, attendance, behavior, and character.

a. Academic Average
   1. Low: score below 75
   2. Medium: score between 75 and 80
   3. High: score above 80
b. Attendance (%)
   1. Low: less than 85%
   2. Moderate: between 85% and 95%
   3. High: above 95%
c. Behavior
   1. Poor: score below 70
   2. Fair: score between 70 and 85
   3. Good: score above 85
d. Character
   1. Poor: score below 70
   2. Fair: score between 70 and 85
   3. Good: score above 85

Before applying the Rough Set method, numerical student data were transformed into categorical form through a discretization process. The results of the data discretization process are presented in Table 3, which shows the categorical transformation of student academic and non-academic attributes.

Table 3. Student Data Discretization Results

Respondents	Year	Academic	Attendance	Behavior	Moral Character	Decision
R1	2021	High	High	Good	Good	Pass
R2	2021	Medium	High	Good	Good	Pass
R3	2021	Medium	High	Good	Good	Pass
R4	2021	Low	Low	Poor	Poor	Fail
R5	2021	Medium	High	Fair	Fair	Pass
R6	2021	Low	High	Good	Good	Pass
R7	2021	Medium	High	Good	Good	Pass
R8	2021	Medium	High	Good	Good	Pass
R9	2021	Medium	High	Good	Good	Pass
R10	2021	Medium	High	Good	Good	Pass
R11	2021	High	High	Fair	Fair	Pass
R12	2021	Medium	High	Good	Good	Pass

Journal of Informatics Management and Information Technology
ISSN 2774-4744 (Media Online)
Vol 6, No 1, January 2026 | Hal 116-127
DOI: 10.47065/jimat.v6i1.961
https://hostjournals.com/jimat

Respondents	Year	Academic	Attendance	Behavior	Moral Character	Decision
R13	2021	Medium	High	Good	Good	Pass
R16	2021	High	High	Good	Good	Pass
R17	2021	Medium	Low	Poor	Poor	Pass
R18	2021	Medium	High	Good	Good	Pass
R19	2021	Medium	High	Good	Good	Pass
R20	2021	High	High	Good	Good	Pass
R21	2021	Medium	High	Good	Good	Pass
R22	2021	Medium	High	Good	Good	Pass
R23	2021	High	High	Good	Good	Pass
R24	2021	Medium	High	Good	Good	Pass
R25	2021	Medium	High	Good	Good	Pass
R26	2021	Medium	High	Good	Good	Pass
R27	2021	Medium	High	Good	Good	Pass
R28	2021	Medium	High	Good	Good	Pass
R29	2021	High	High	Good	Good	Pass
R30	2021	High	High	Good	Good	Pass
R31	2021	High	High	Good	Good	Pass
R32	2022	High	High	Good	Good	Pass
R33	2022	High	High	Good	Good	Pass
R34	2022	Medium	High	Good	Good	Pass
R35	2022	High	High	Good	Good	Pass
R36	2022	Medium	High	Good	Good	Pass
R37	2022	Medium	High	Good	Good	Pass
R38	2022	Medium	High	Good	Good	Pass
R39	2022	Medium	High	Good	Good	Pass
R40	2022	Medium	High	Good	Good	Pass
R41	2022	Medium	High	Good	Good	Pass
R42	2022	High	High	Good	Good	Pass
R43	2022	Medium	High	Good	Good	Pass
R44	2022	Medium	High	Good	Good	Pass
R45	2022	High	High	Good	Good	Pass
R46	2022	Medium	High	Good	Good	Pass
R47	2022	Medium	High	Good	Good	Pass
R48	2022	Medium	High	Good	Good	Pass
R49	2022	High	High	Good	Good	Pass
R50	2022	High	High	Good	Good	Pass
R51	2022	High	High	Good	Good	Pass
R52	2022	High	High	Good	Good	Pass
R53	2022	High	High	Good	Good	Pass
R54	2022	High	High	Good	Good	Pass
R55	2022	Medium	High	Good	Good	Pass
R56	2022	High	High	Good	Good	Pass
R57	2022	Medium	High	Good	Good	Pass
R58	2022	Medium	High	Good	Good	Pass
R59	2022	High	High	Good	Good	Pass
R60	2023	Medium	High	Good	Good	Pass
R61	2023	High	Low	Poor	Poor	Pass
R62	2023	Medium	High	Good	Good	Pass
R63	2023	Medium	High	Good	Good	Pass
R64	2023	Low	Moderate	Fair	Fair	Fail
R65	2023	Medium	Moderate	Poor	Fair	Pass
R66	2023	Low	High	Good	Good	Pass
R67	2023	Medium	High	Good	Good	Pass
R68	2023	Medium	High	Good	Good	Pass
R69	2023	Medium	High	Good	Good	Pass
R70	2023	Medium	High	Good	Good	Pass
R71	2023	Medium	High	Good	Good	Pass
R72	2023	Medium	High	Good	Good	Pass
R73	2023	Medium	High	Good	Good	Pass
R74	2023	Medium	High	Good	Good	Pass
R75	2023	Medium	High	Good	Good	Pass

ISSN 2774-4744 (Media Online)
Vol 6, No 1, January 2026 | Hal 116-127
DOI: 10.47065/jimat.v6i1.961
https://hostjournals.com/jimat

Respondents	Year	Academic	Attendance	Behavior	Moral Character	Decision
R76	2023	Medium	High	Good	Good	Pass
R77	2023	Medium	High	Good	Good	Pass
R78	2023	Medium	High	Good	Good	Pass
R79	2023	Medium	High	Good	Good	Pass
R80	2023	Medium	High	Good	Good	Pass
R81	2024	Medium	High	Good	Good	Pass
R82	2024	Medium	High	Good	Good	Pass
R83	2024	Medium	Low	Fair	Fair	Pass
R84	2024	High	High	Good	Good	Pass
R85	2024	Medium	High	Good	Good	Pass
R86	2024	Medium	High	Good	Good	Pass
R87	2024	High	High	Good	Good	Pass
R88	2024	Medium	High	Good	Good	Pass
R89	2024	Medium	High	Good	Good	Pass
R90	2024	High	High	Good	Good	Pass
R91	2024	High	High	Good	Good	Pass
R92	2024	High	High	Good	Good	Pass
R93	2024	High	High	Good	Good	Pass
R94	2024	Low	High	Fair	Fair	Fail
R95	2024	Medium	High	Good	Good	Pass
R96	2024	Medium	High	Good	Good	Pass
R97	2024	Medium	High	Good	Good	Pass
R98	2024	Medium	High	Good	Good	Pass
R99	2024	High	High	Good	Good	Pass
R100	2024	Medium	High	Good	Good	Pass
R101	2024	Medium	High	Good	Good	Pass
R102	2024	High	High	Good	Good	Pass
R103	2024	Medium	High	Good	Good	Pass
R104	2024	Medium	High	Good	Good	Pass
R105	2024	Medium	Moderate	Good	Good	Pass
R106	2024	Medium	High	Good	Good	Pass
R107	2024	Medium	High	Good	Good	Pass
R108	2024	Medium	High	Good	Good	Pass

3.2.3. Data Processing Using Rosetta

The student graduation classification process is carried out using Rosetta software, which is based on the Rough Set method. In this stage, student academic data that has been discretized is imported into Rosetta for analysis. Next, Rosetta generates a number of decision rules that represent patterns of correlation between variables such as academic average, attendance, behavior, and character with student graduation decisions. The initial interface of the Rosetta software after the dataset is loaded is shown in Figure 3.

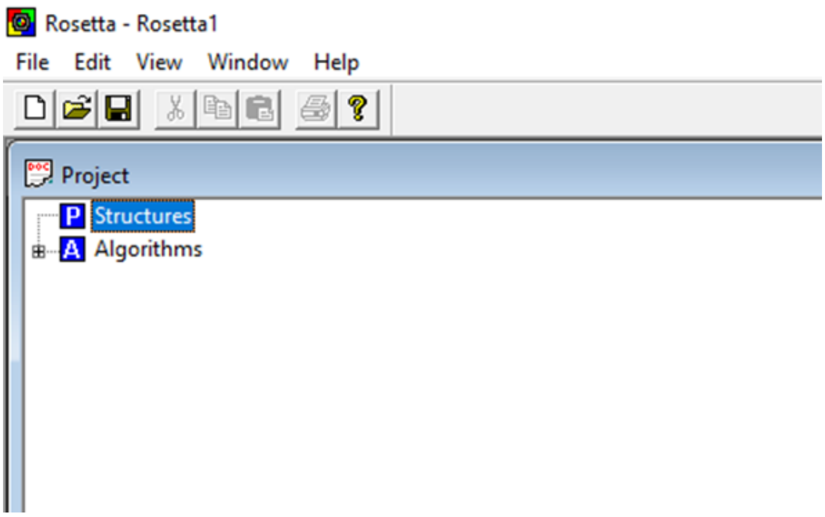
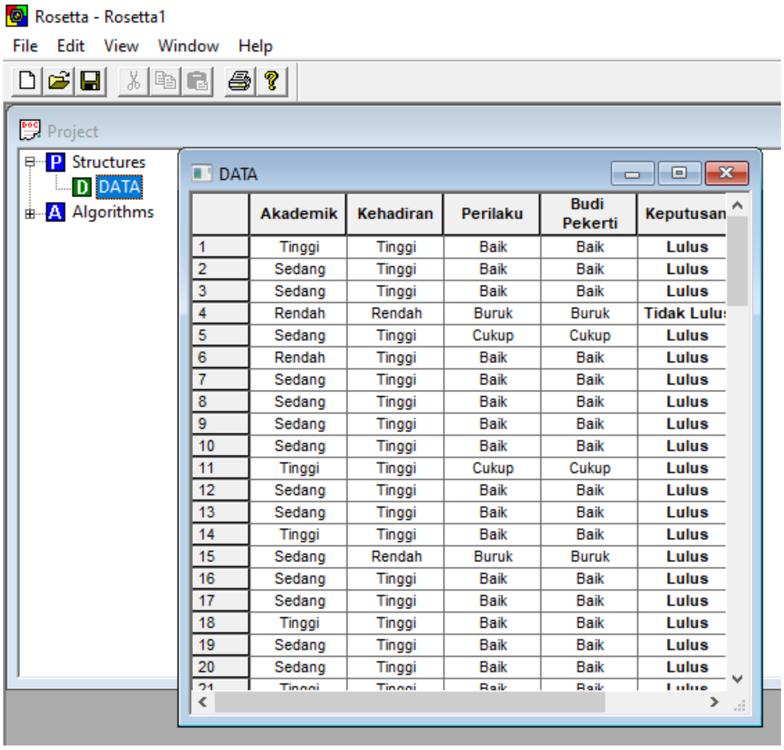


Figure 3. Initial Display

Figure 4 shows the student dataset that has been successfully imported into the Rosetta software for analysis.

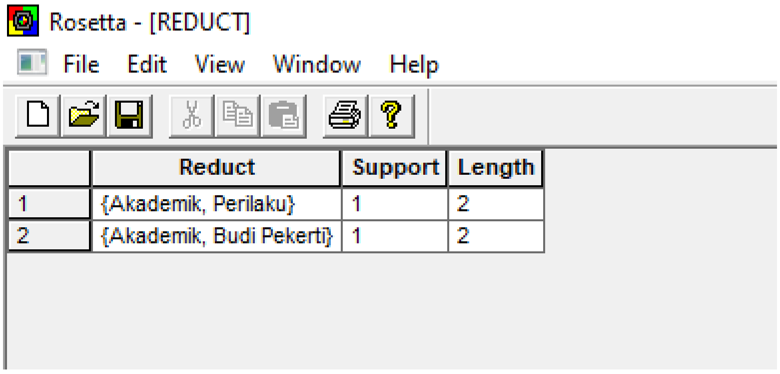
Journal of Informatics Management and Information Technology
ISSN 2774-4744 (Media Online)
Vol 6, No 1, January 2026 | Hal 116-127
DOI: 10.47065/jimat.v6i1.961
https://hostjournals.com/jimat



	Akademik	Kehadiran	Perilaku	Budi Pekerti	Keputusan
1	Tinggi	Tinggi	Baik	Baik	Lulus
2	Sedang	Tinggi	Baik	Baik	Lulus
3	Sedang	Tinggi	Baik	Baik	Lulus
4	Rendah	Rendah	Buruk	Buruk	Tidak Lulu:
5	Sedang	Tinggi	Cukup	Cukup	Lulus
6	Rendah	Tinggi	Baik	Baik	Lulus
7	Sedang	Tinggi	Baik	Baik	Lulus
8	Sedang	Tinggi	Baik	Baik	Lulus
9	Sedang	Tinggi	Baik	Baik	Lulus
10	Sedang	Tinggi	Baik	Baik	Lulus
11	Tinggi	Tinggi	Cukup	Cukup	Lulus
12	Sedang	Tinggi	Baik	Baik	Lulus
13	Sedang	Tinggi	Baik	Baik	Lulus
14	Tinggi	Tinggi	Baik	Baik	Lulus
15	Sedang	Rendah	Buruk	Buruk	Lulus
16	Sedang	Tinggi	Baik	Baik	Lulus
17	Sedang	Tinggi	Baik	Baik	Lulus
18	Tinggi	Tinggi	Baik	Baik	Lulus
19	Sedang	Tinggi	Baik	Baik	Lulus
20	Sedang	Tinggi	Baik	Baik	Lulus

Figure 4. Display of Successfully Inputted Data

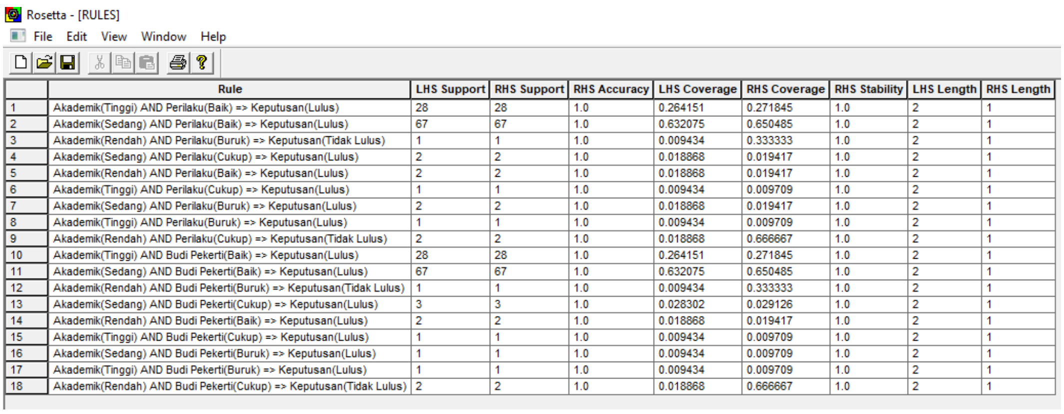
The results of the attribute reduction process using the Exhaustive Reduct method are presented in Figure 5.



	Reduct	Support	Length
1	{Akademik, Perilaku}	1	2
2	{Akademik, Budi Pekerti}	1	2

Figure 5. Reduction Results

The decision rules generated from the reduced attributes using the Rough Set method are shown in Figure 6.



	Rule	LHS Support	RHS Support	RHS Accuracy	LHS Coverage	RHS Coverage	RHS Stability	LHS Length	RHS Length
1	Akademik(Tinggi) AND Perilaku(Baik) => Keputusan(Lulus)	28	28	1.0	0.264151	0.271845	1.0	2	1
2	Akademik(Sedang) AND Perilaku(Baik) => Keputusan(Lulus)	67	67	1.0	0.632075	0.650485	1.0	2	1
3	Akademik(Rendah) AND Perilaku(Buruk) => Keputusan(Tidak Lulus)	1	1	1.0	0.009434	0.333333	1.0	2	1
4	Akademik(Sedang) AND Perilaku(Cukup) => Keputusan(Lulus)	2	2	1.0	0.018868	0.019417	1.0	2	1
5	Akademik(Rendah) AND Perilaku(Baik) => Keputusan(Lulus)	2	2	1.0	0.018868	0.019417	1.0	2	1
6	Akademik(Tinggi) AND Perilaku(Cukup) => Keputusan(Lulus)	1	1	1.0	0.009434	0.009709	1.0	2	1
7	Akademik(Sedang) AND Perilaku(Buruk) => Keputusan(Lulus)	2	2	1.0	0.018868	0.019417	1.0	2	1
8	Akademik(Tinggi) AND Perilaku(Buruk) => Keputusan(Lulus)	1	1	1.0	0.009434	0.009709	1.0	2	1
9	Akademik(Rendah) AND Perilaku(Cukup) => Keputusan(Tidak Lulus)	2	2	1.0	0.018868	0.666667	1.0	2	1
10	Akademik(Tinggi) AND Budi Pekerti(Baik) => Keputusan(Lulus)	28	28	1.0	0.264151	0.271845	1.0	2	1
11	Akademik(Sedang) AND Budi Pekerti(Baik) => Keputusan(Lulus)	67	67	1.0	0.632075	0.650485	1.0	2	1
12	Akademik(Rendah) AND Budi Pekerti(Buruk) => Keputusan(Tidak Lulus)	1	1	1.0	0.009434	0.333333	1.0	2	1
13	Akademik(Sedang) AND Budi Pekerti(Cukup) => Keputusan(Lulus)	3	3	1.0	0.028302	0.029126	1.0	2	1
14	Akademik(Rendah) AND Budi Pekerti(Baik) => Keputusan(Lulus)	2	2	1.0	0.018868	0.019417	1.0	2	1
15	Akademik(Tinggi) AND Budi Pekerti(Cukup) => Keputusan(Lulus)	1	1	1.0	0.009434	0.009709	1.0	2	1
16	Akademik(Sedang) AND Budi Pekerti(Buruk) => Keputusan(Lulus)	1	1	1.0	0.009434	0.009709	1.0	2	1
17	Akademik(Tinggi) AND Budi Pekerti(Buruk) => Keputusan(Lulus)	1	1	1.0	0.009434	0.009709	1.0	2	1
18	Akademik(Rendah) AND Budi Pekerti(Cukup) => Keputusan(Tidak Lulus)	2	2	1.0	0.018868	0.666667	1.0	2	1

Figure 6. Generate Rules Results

Based on the results of generating rules using the Exhaustive Reduct method in Rosetta software, 18 rules were obtained from the combination of Academic and Behavior attributes as well as Academic and Character attributes. Each rule shows the logical relationship between the combination of input conditions and the final decision, namely Pass or

ISSN 2774-4744 (Media Online)
Vol 6, No 1, January 2026 | Hal 116-127
DOI: 10.47065/jimat.v6i1.961
https://hostjournals.com/jimat

Fail. All rules have an accuracy level of 1.0, which means that there is no ambiguity in decision making for each combination of attributes. In other words, each combination of attribute values on the left side of the rule consistently produces the same decision on the right side. The rule “High Academic and Good Behavior results in a Pass decision” is supported by 28 data points, and the rule “Moderate Academic and Good Behavior results in a Pass decision” is supported by 67 data points. This shows that most participants with high or moderate academic scores who also have good behavior tend to be declared passed. There are also several rules with a small amount of support, such as the combination of Low Academic Performance and Poor Behavior resulting in a Fail decision, but they still have perfect accuracy.

3.2.4. Discernibility Matrix Analysis and Attribute Reduction

The discernibility matrix is used to identify attributes that play a role in distinguishing objects with different decisions. Through this analysis, attributes that do not contribute significantly to the classification process can be eliminated through a reduction process. The results of attribute reduction obtained using the Exhaustive Reduct method in Rosetta software show that academic attributes are the main factor in determining graduation. In addition, behavioral and moral attributes also emerged as important attributes in several reduction combinations. Attributes of attendance under certain conditions can be eliminated without reducing the accuracy of the decision. These results show that student graduation decisions are not solely determined by academic achievement, but are also influenced by aspects of attitude and character.

3.2.5. Formulation of Decision Rules

Decision rules are formed based on the results of attribute reduction. These rules represent the logical relationship between condition attributes and student graduation decisions.
Some of the main rules generated include:

a. Students with high academic performance and good behavior are classified as passing.
b. Students with moderate academic performance and good character tend to pass.
c. Students with low academic performance and poor behavior are classified as failing.

These rules are deterministic, where each combination of condition attributes produces one definite decision. This shows that the Rough Set method is capable of producing a classification model that is clear and easy to interpret.

3.3 Model Implementation and Testing

The Rough Set method was implemented using Microsoft Excel as a data preprocessing tool and Rosetta as the main analysis tool. Excel was used to calculate average values, discretization, and data compilation, while Rosetta was used to form reducts and decision rules. Model testing shows that the resulting decision rules are consistent and do not cause conflicts between decisions. This indicates that the Rough Set method is able to effectively classify student graduation based on the attributes used. The overall implementation flow of the Rough Set method for student graduation classification is illustrated in Figure 7.

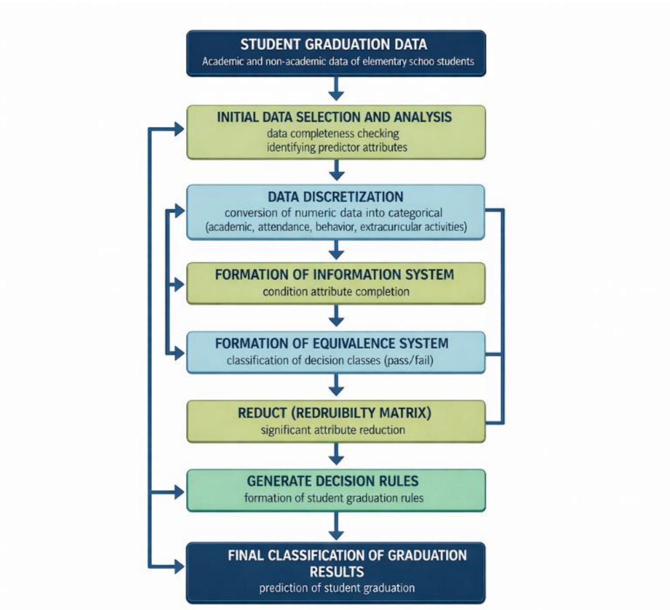


Figure 7. Rough Set Implementation Flow in Student Graduation Classification

3.2 Discussion

The results of this study prove that the Rough Set method is effective when applied to the classification of elementary school student graduation based on academic data. Academic attributes play a dominant role, but behavioral and moral attributes have been proven to strengthen classification decisions under certain conditions. These findings are consistent

ISSN 2774-4744 (Media Online)
Vol 6, No 1, January 2026 | Hal 116-127
DOI: 10.47065/jimat.v6i1.961
https://hostjournals.com/jimat

with Samaray's (2022) research, which states that Rough Set is capable of producing explicit and easy-to-understand decision rules. Furthermore, these results are also in line with Zuhdi (2022), who emphasizes the superiority of Rough Set in identifying important attributes in decision-making systems. The main contribution of this study lies in the application of the Rough Set method in the context of elementary education by simultaneously considering academic and character aspects of students. Thus, the resulting model can serve as an alternative to support more objective and data-driven decision-making regarding student graduation.

4. CONCLUSION

This study shows that the Rough Set method can be effectively applied in classifying elementary school student graduation based on academic and non-academic data. Through the stages of data discretization, decision system formation, attribute reduction, and decision rule generation, the Rough Set method is able to produce a classification model that is consistent and easy to understand. The results of the study indicate that academic attributes are the main factor in determining student graduation, but behavioral and moral attributes also play a role in strengthening classification decisions under certain conditions. This confirms that student graduation assessment does not only depend on academic achievement, but also needs to consider aspects of attitude and character proportionally. The decision rules generated are deterministic and do not cause conflicts between decision classes, so they can be used to support more objective and data-based graduation decisions. Thus, the Rough Set method can be a relevant alternative approach for schools in conducting systematic and transparent student graduation evaluations. However, this study still has limitations in terms of the amount of data and the scope of the research object, which only covers one school in a certain period of time. In addition, this study has not compared the performance of the Rough Set method with other classification methods. Therefore, further research is recommended to expand the amount and variety of data, add supporting attributes, and compare the Rough Set method with other classification approaches in order to obtain more comprehensive and generalizable results.

REFERENCES

[1] K. Kuczera and D. Dziembek, “Application of Rough Set Theory to Improve the Efficiency of Higher Education Systems,” in *European Conference on Artificial Intelligence*, Springer, 2024, pp. 237–249, doi: 10.1007/978-3-031-78468-2_18
[2] F. Ekundayo, I. Atoyebi, A. Soyele, and E. Ogunwobi, “Predictive analytics for cyber threat intelligence in fintech using big data and machine learning,” *Int J Res Publ Rev*, vol. 5, no. 11, pp. 1–15, 2024, doi: 10.55248/gengpi.5.1124.3352
[3] S. A. Putri, N. Selayanti, M. Kristanaya, M. P. Azzahra, M. G. Navsih, and K. M. Hindrayani, “Penerapan Machine Learning Algoritma Random Forest Untuk Prediksi Penyakit Jantung,” in *Prosiding Seminar Nasional Sains Data*, 2024, pp. 895–906, doi: 10.33005/senada.v4i1.376
[4] G. Saputri, “Using The Borda Methode On A Decision Support System,” *J. Data Anal. Information, Comput. Sci.*, vol. 1, no. 1, pp. 19–24, 2024, doi: 10.59407/jdaics.v1i1.422
[5] A. Arif, “Penerapan Metode Extreme Programming Pada E-Voting Pemilihan Ketua Unit Kegiatan Mahasiswa (UKM) Sekolah Tinggi Teknologi XYZ,” *J. Sist. dan Teknol. Inf.*, vol. 9, no. 2, p. 234, 2021, doi: 10.26418/justin.v9i2.44266.
[6] N. Nurdiansyah, F. S. Febriyan, Z. Gesit, and D. Amanta, “Mental Health Analysis to Prevent Mental Disorders in Students Using The K-Nearest Neighbor (K-NN),” *MALCOM Indones. J. Mach. Learn. Comput. Sci.*, vol. 5, no. January, pp. 1–9, 2025, doi: https://doi.org/10.57152/malcom.v5i1.1537.
[7] A. E. Widjaja, A. Fransisko, and C. A. Haryani, “Text Mining Application with K-Means Clustering to Identify Sentiments and Popular Topics : a Case Study of the three Largest Online Marketplaces in Indonesia,” *Inform. J. Ilmu Komput.*, vol. 4, no. 4, pp. 441–453, 2023, doi: 10.47738/jads.v4i4.134
[8] S. Dewi, A. Kresnawati, S. Sopyanti, and A. Sulmainah, “Mapping Library User Behavior Base On K-Means Clustering Of Ma ’ soem University Student Pemetaan Perilaku Pengguna Perpustakaan Berbasis K-Means Pada Mahasiswa Universitas Ma ’ soem,” *Bimaster Bul. Ilm. Mat. Stat. dan Ter.*, vol. 5, no. 2, pp. 130–136, 2025, doi: 10.57152/ijirse.v5i2.2238
[9] S. Howay and S. Suhirman, “Comparison of SVM, NBC, and KNN Classification Methods in Determining Students’ Majors at SMK N02 Manokwari,” *J. Comput. Sci. Technol. Stud.*, vol. 5, no. 1, pp. 15–23, 2023, doi: 10.32996/jcsts.2023.5.1.3.
[10] M. T. Hidayat, M. Arifin, and S. Muzid, “Prediction Sentiment Analysis Grab Reviews using SVM Linear Based Streamlit,” *Indones. J. Comput. Cybern. Syst.*, vol. 19, no. 2, pp. 1–12, 2025, doi: 10.22146/ijccs.104924.
[11] M. Herviany, S. Putri Delima, T. Nurhidayah, and Kasini, “Comparison of K-Means and K-Medoids Algorithms for Grouping Landslide Prone Areas in West Java Province,” *MALCOM Indones. J. Mach. Learn. Comput. Sci.*, vol. 1, no. 1, pp. 34–40, 2021.
[12] H. Mustakim and S. Priyanta, “Aspect-Based Sentiment Analysis of KAI Access Reviews Using NBC and SVM,” *IJCCS (Indonesian J. Comput. Cybern. Syst.*, vol. 16, no. 2, p. 113, 2022, doi: 10.22146/ijccs.68903.
[13] H. Sunaryanto, M. A. Hasan, and G. Guntoro, “Classification Analysis of Unilak Informatics Engineering Students Using Support Vector Machine (SVM), Iterative Dichotomiser 3 (ID3), Random Forest and K-Nearest Neighbors (KNN),” *IT J. Res. Dev.*, vol. 7, no. 1, pp. 36–42, 2022, doi: 10.25299/itjrd.2022.8912.
[14] N. A. Ochuba, O. O. Amoo, E. S. Okafor, O. Akinrinola, and F. O. Usman, “Strategies for leveraging big data and analytics for business development: a comprehensive review across sectors,” *Comput. Sci. IT Res. J.*, vol. 5, no. 3, pp. 562–575, 2024.
[15] A. Pambudi and S. Suprapto, “Effect of Sentence Length in Sentiment Analysis Using Support Vector Machine and Convolutional Neural Network Method,” *IJCCS (Indonesian J. Comput. Cybern. Syst.*, vol. 15, no. 1, p. 21, 2021, doi: 10.22146/ijccs.61627.
[16] S. Samaray, “Implementasi Algoritma Rough Set dengan Software Rosetta untuk Prediksi Hasil Belajar,” *J. Eksplora Inform.*, vol. 11, no. 1, pp. 57–66, 2022, doi: 10.30864/eksplora.v11i1.498.
[17] A. A. Ahmed *et al.*, “Arabic text detection using rough set theory: Designing a novel approach,” *IEEE Access*, vol. 11, pp. 68428–68438, 2023, doi: 10.1109/ACCESS.2023.3278272

ISSN 2774-4744 (Media Online)
Vol 6, No 1, January 2026 | Hal 116-127
DOI: 10.47065/jimat.v6i1.961
https://hostjournals.com/jimat

[18] N. F. Munazhif, G. J. Yanris, and M. N. S. Hasibuan, "Implementation of the K-Nearest Neighbor (kNN) Method to Determine Outstanding Student Classes," *SinkrOn*, vol. 8, no. 2, pp. 719–732, 2023, doi: 10.33395/sinkron.v8i2.12227.

[19] J. Maulani and M. Sari, "Komparasi Metode K-Nearest Neighbor (Knn) Dengan Support Vector Machine (Svm) Terhadap Tingkat Akurasi Klasifikasi Kualitas Air," *Smart Comp Jurnalnya Orang Pint. Komput.*, vol. 12, no. 2, pp. 430–435, 2023, doi: 10.30591/smartcomp.v12i2.4205.

[20] S. Suryanto and W. Andriyani, "Sentiment Analysis of X Platform on Viral 'Fufufafa' Account Issue in Indonesia Using SVM," *IJCCS (Indonesian J. Comput. Cybern. Syst.*, vol. 19, no. 1, p. 95, 2025, doi: 10.22146/ijccs.104158.