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MACHINE LEARNING-BASED PREDICTION OF MATHEMATICAL HOTS: WHICH FACTORS MATTER MOST?

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Abstract

Junior high school students' mathematical Higher Order Thinking Skills (HOTS) in Indonesia remain relatively low, while studies applying machine learning to identify the factors influencing HOTS are still limited. This study aims to develop a predictive model of students' mathematical HOTS, identify its key predictors, and determine the best-performing algorithm. A descriptive quantitative approach was employed with 391 seventh- and eighth-grade students from a state Islamic junior high school (MTs) in South Jakarta. Data were collected through a questionnaire measuring internal and external learning factors and a HOTS-based essay test, then analyzed using Chi-Square feature selection and seven supervised machine learning algorithms in Orange Data Mining. The results identified physiological condition, fatigue, and intelligence as the strongest predictors of HOTS, whereas school environment and learning motivation contributed minimally. Among the algorithms, Naïve Bayes achieved the most consistent predictive performance. These findings provide data-driven evidence for designing instructional strategies that support students' mathematical HOTS.
Keywords: *Higher Order Thinking Skills (HOTS); machine learning; Naïve Bayes; physiological condition*

Abstrak

Kemampuan Higher Order Thinking Skills (HOTS) matematis siswa SMP di Indonesia masih relatif rendah, sementara penelitian yang memanfaatkan *machine learning* untuk mengidentifikasi faktor-faktor yang memengaruhinya masih terbatas. Penelitian ini bertujuan mengembangkan model prediksi HOTS matematis siswa, mengidentifikasi faktor-faktor dominan yang memengaruhinya, serta menentukan algoritma dengan kinerja terbaik. Penelitian menggunakan pendekatan kuantitatif deskriptif dengan melibatkan 391 siswa kelas VII dan VIII di salah satu MTs Negeri di Jakarta Selatan. Data dikumpulkan melalui angket faktor internal dan eksternal serta tes uraian berbasis HOTS, kemudian dianalisis menggunakan seleksi fitur Chi-Square dan tujuh algoritma *supervised machine learning* pada Orange Data Mining. Hasil menunjukkan bahwa kondisi fisiologis, kelelahan, dan inteligensi merupakan prediktor utama HOTS matematis, sedangkan lingkungan sekolah dan motivasi belajar memberikan kontribusi yang minimal. Di antara seluruh algoritma, Naïve Bayes menunjukkan kinerja prediksi yang paling konsisten. Temuan ini memberikan dasar berbasis data untuk merancang strategi pembelajaran yang mendukung pengembangan HOTS matematis siswa.
Kata kunci: *Higher Order Thinking Skills* (HOTS), kondisi fisiologis, *machine learning*, *Naïve Bayes*

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INTRODUCTION

Education is an essential process in developing human potential to become qualified individuals who are able to face the challenges of modern development. In the context of modern education, improving the quality of human resources has become a major necessity in responding to global competition (Haryanto, 2020). One effort to improve the quality of human resources is carried out through mathematics education. Mathematics plays an important role in developing logical, critical, systematic, and creative thinking skills because it serves as the foundation for the advancement of science and technology. In addition to functioning as a means of developing reasoning and problem-solving abilities, mathematics learning is also directed toward fostering students' higher-order thinking skills (HOTS). HOTS refers to thinking skills involving the abilities to analyze, evaluate, and create solutions to problems (Krathwohl, 2002). In mathematics learning, HOTS is considered an essential competency that students must possess in order to solve non-routine and contextual problems logically and systematically in accordance with curriculum demands and 21st-century learning goals.

Various studies have shown that the mathematical HOTS of junior high school students in Indonesia are still relatively low. Results from the Organisation for Economic Co-operation and Development through the Programme for International Student Assessment (PISA) 2022 indicated that Indonesian students achieved an average creative thinking score of only 19 out of 60 points, which is below the OECD average of 33 points (OECD, 2022). In addition, only approximately 31% of Indonesian students reached the baseline proficiency level in creative thinking skills. The creative thinking abilities assessed in PISA include generating ideas, developing alternative solutions, and evaluating as well as improving ideas. These abilities are part of HOTS, particularly at the creating level (C6) in the revised Bloom's Taxonomy. The low achievement indicates that Indonesian students' higher-order thinking skills still need significant improvement, especially in the aspects of analysis, evaluation, and creation. Dewi et al. (2023) found that most students experienced difficulties in solving HOTS-based problems, particularly in algebra topics. These difficulties included understanding problem statements, determining appropriate solution strategies, and performing suitable mathematical operations. Similarly, Thoyip et al. (2024) revealed that students encountered difficulties in understanding problems presented in graphs, images, and lengthy story problems, which hindered their ability to analyze and solve HOTS-oriented mathematical problems.

These national gaps are also reflected at the institutional level. Based on a preliminary interview conducted with a mathematics teacher at State Islamic Junior High School 4 Jakarta on November 28, 2025, it was found that students' mathematical HOTS were still categorized as moderate to low. Students experienced difficulties in understanding contextual problems, analyzing mathematical situations, and relating mathematical concepts to real-life contexts. In addition, students were not accustomed to solving non-routine problems and tended to focus only on routine example problems provided by teachers. The teacher explained that students' conceptual understanding, study habits, psychological readiness, and variations in teaching methods were among the factors influencing the low level of HOTS. These findings indicate the need for an analytical approach capable of identifying dominant factors more effectively and accurately to assist teachers in understanding students' learning conditions.

The low level of mathematical HOTS is influenced by various internal and external factors. Internal factors include learning motivation, learning interest, conceptual understanding, study habits, and students' psychological readiness in learning mathematics. Meanwhile, external factors include the learning environment, teaching methods, family support, and the use of instructional media and technology (Nabillah & Abadi, 2019). Afni & Nurhayati. (2022) explained that environmental, psychological, and intellectual characteristics significantly influence students' HOTS. Najahah et al. (2022) identified several types of errors made by students in solving HOTS problems, including reading errors, comprehension errors, transformation errors, process skill errors, and encoding errors. Furthermore, Manik et al. (2020) stated that students were not accustomed to solving problem-based essay questions, causing difficulties in determining appropriate solution strategies. Khotimah (2019) also found that teachers, teacher-student relationships, and family economic conditions contributed to students' mathematics learning outcomes.

Technological advancements in education provide new opportunities for analyzing educational data, one of which is through the implementation of Machine Learning (ML). ML is a computational method that enables systems to learn patterns from historical data in order to generate predictions automatically without being explicitly programmed (Mohri et al., 2018). In education, the application of ML is known as Educational Data Mining (EDM), which refers to the process of extracting meaningful patterns and information from educational data to support learning processes. Previous studies have demonstrated the potential of ML in educational data analysis. Setiyani et al. (2020) applied the Naïve Bayes method to predict students' graduation timeliness and found that the method was capable of making predictions based on students' academic data attributes. Other studies also showed that ML could be used to predict students' understanding of certain courses by identifying dominant factors affecting the learning process (Raharjo & Windarto, 2021). Moreover, ML has been widely implemented in other fields such as healthcare and agriculture, demonstrating its flexibility and effectiveness in data analysis and prediction tasks (Watratan, 2020).

Previous studies have shown immense strengths in mapping out educational barriers and providing robust frameworks for conventional statistical validation. Although various studies have applied ML in education, research specifically identifying factors influencing junior high school students' mathematical HOTS using ML approaches remains limited. Most previous studies focused only on analyzing students' difficulties or examining the influence of certain factors on HOTS using conventional statistical approaches. In addition, previous studies have rarely integrated HOTS test results with non-test data consisting of students' internal and external factors to develop predictive models of mathematical HOTS among junior high school students. Therefore, the novelty of this study lies in the use of a Machine Learning approach to develop a predictive model of students' mathematical HOTS while simultaneously identifying the dominant factors influencing HOTS through the integration of test and non-test data. In this study, the analysis process was conducted using Orange Data Mining, which offers advantages such as interactive visual interfaces and ease of use in classification, prediction, and model evaluation processes.

Based on the explanations above, this study focuses on the use of Machine Learning to identify factors influencing junior high school students' mathematical HOTS using Orange Data Mining. This study aims to develop a predictive model of students' mathematical HOTS levels, identify the dominant factors influencing mathematical HOTS, and determine the algorithm with the best performance in predicting students' mathematical HOTS levels. This study is expected to contribute to the development of Machine Learning applications in mathematics education, particularly in the process of identifying and predicting students' mathematical HOTS in a more effective, accurate, and data-driven manner.

METHOD

This study employed a descriptive quantitative research design to identify the factors influencing students' mathematical Higher Order Thinking Skills (HOTS) using machine learning techniques. The study was conducted at one of the State Islamic Junior High Schools located in South Jakarta during the odd semester of the 2025/2026 academic year. The population of this study consisted of all seventh-grade students' who had studied HOTS-based comparison and scale materials. The sample was selected using purposive sampling techniques by considering classes that had received HOTS-based learning. The minimum number of samples required in this study was 391 students'. This technique was used to obtain data that were relevant to the objectives of the study.

The instruments used in this study consisted of test and non-test instruments. The non-test instrument was a questionnaire developed using a five-point Likert scale ranging from 1 (Strongly

Disagree) to 5 (Strongly Agree). The questionnaire was designed to measure several factors affecting students' mathematical HOTS, namely learning interest, learning motivation, students' intelligence, physiological condition, fatigue, school environment, and family environment. Meanwhile, the test instrument consisted of HOTS-based essay questions on comparison and scale materials, which were designed to measure students' abilities in analysing (C4), evaluating (C5), and creating (C6). The instruments were validated through content validity by experts using Lawshe's Content Validity Ratio (CVR), followed by empirical validity and reliability testing using SPSS version 25. The empirical validity test employed Pearson Product Moment correlation, while reliability testing used Cronbach's Alpha coefficient.

The data collection techniques used in this study were test and non-test techniques. The test instrument was administered to measure students' mathematical HOTS achievement, whereas the questionnaire was distributed to identify academic and non-academic factors influencing HOTS. Prior to the main research, the instruments were tried out on 31 respondents outside the research sample to examine the validity, reliability, item difficulty level, and discrimination index of the instruments. The results showed that the instruments met the required validity and reliability criteria and were appropriate for use in the research process.

The collected data were processed and analyzed using Microsoft Excel, SPSS version 25, and Orange Data Mining software. The normality test was conducted using the Kolmogorov–Smirnov method. Furthermore, the machine learning approach applied in this study was supervised learning, particularly classification techniques. Several algorithms were implemented and compared, namely Naïve Bayes, k-Nearest Neighbour (kNN), Decision Tree, Random Forest, Support Vector Machine (SVM), Logistic Regression, and Neural Network. To provide a clearer understanding of the classification methods applied in this study, several mathematical formulations of the machine learning algorithms are presented below. These formulas describe the basic concepts and calculation mechanisms used by each algorithm in the classification and prediction processes.

1. The Naïve Bayes algorithm is formulated as follows (Saputra & Kristayanti, 2022):

$$P(c|X) = \frac{P(X|C)P(c)}{P(x)} \qquad (1)$$

Where:

X	: Data with an unknown class
c	: Hypothesis that the data belong to a spesific class
$P(c\|X)$	: Posterior probability of hypothesis c given data X
$P(c)$	: Prior probability of hypothesis c
$P(x\|c)$	: Conditional probability of data X given class c
$P(x)$	: Probability of data X

2. The k-Nearest Neighbour (kNN) algorithm is formulated as follows (Saputra & Kristayanti, 2022):

$$d(P, Q) = \sqrt{\sum_{i=1}^{n} (p_i - q_i)^2} \qquad (2)$$

Where:

$d(P, Q)$: Distance between samples

p_i : Sample data value

q_i : Input data value of the i-th variable

n : Number of samples

3. The Decision Tree algorithm is formulated as follows (Saputra & Kristayanti, 2022):

$$IG = (Y, X) = E(Y) - E(Y|X) \qquad (3)$$

Where:

IG : Information gain

$E(Y)$: Entropy of the target feature

$E(Y|X)$: Average entropy of the predictor feature toward the target feature

X : Predictor feature

Y : Target feature

4. The Random Forest algorithm is formulated as follows (Saputra & Kristayanti, 2022):

$$Gini = 1 - \sum_{i=1}^{C} (p_i)^2 \qquad (4)$$

Where:

p_i : Probability comparison of positive or negative target feature outcomes

$\sum_{i=1}^{C}$: Total comparison of positive and negative target feature outcomes

5. The Support Vector Machine (SVM) algorithm is formulated as follows (Putra et al., 2020):

$$w.x + b = 0 \qquad (5)$$

Where:

w : Weight vector

x : Input data

b : Bias

Optimization function:

$$min \frac{1}{2} \|w\|^2 \qquad (6)$$

Subject to:

$$y_i(w.x_i + b) \geq 1 \qquad (7)$$

Where:

y_i : Class label (+1 or -1)

6. The Logistic Regression algorithm is formulated as follows (Kurniawan, 2020):

$$f(x) = \frac{1}{1+e^{-x}} \qquad (8)$$

Where:

e : Euler's constant (approximately 2.71828)

7. The Neural Network algorithm is formulated as follows (Saputra & Kristayanti, 2022):

$$y = w_1x_1 + w_2x_2 + w_3x_3 + b \quad (9)$$

Where:
y : Prediction result
w : Weight
x : Feature
b : Bias

Feature selection was conducted using the filter method to identify the most influential variables affecting students' mathematical HOTS. Model evaluation was carried out using confusion matrix analysis by considering the values of accuracy, precision, and recall determining the best-performing algorithm. These evaluation metrics were used to measure the effectiveness of the classification models in predicting students' mathematical HOTS categories. The formulas used in this study are presented as follows (Saputra & Kristayanti, 2022):

1. Accuracy formula

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (10)$$

Where:
TP : True Positive
TN : True Negative
FP : False Positive
FN : False Negative

2. Presicion formula

$$Precision = \frac{TP}{TP+FP} \quad (11)$$

Where:
TP : True Positive
FP : False Positive

3. Recall formula

$$Recall = \frac{TP}{TP+FN} \quad (12)$$

TP : True Positive
FN : False Negative

Table 1. Factors Measured

Variable	Indicators	Item Numbers	Total Items
Learning Interest	Feeling happy	1, 2	2
	Atraction	3, 4, 5	3
	Involvement	6, 7	2
Learning Motivation	Willingness	8, 9, 10	3
	Encouragement	11, 12	2
Student's Intelligence	Self-adjustment	13, 14	2
	Information processing	15, 16, 17, 18, 19	5

Physiological Condition	Sensory function	20, 21, 22, 23, 24	5
	Physical health	25, 26, 27	3
Fatigue	Physical fatigue	28, 29, 30	3
	Mental fatigue	31, 32, 33, 34	4
School Environment	Relationships	35, 36, 37	3
	Learning facilities	38, 39, 40, 41	4
	Teaching methods	42, 43, 44	3
	School schedule	45, 46, 47	3
	School building condition	48, 49, 50, 51	4
	Learning methods	52, 53	2
Familiy Environment	Parenting style	54, 55, 56	3
	Family relationships	57, 58	2
	Home atmosphere	59, 60	2
	Economic condition	61, 62, 63	3
	Parents understanding	64, 65, 66	3
	Culutural backgorund	67, 68	2

Based on Table 1, it is shown that this study comprehensively measured seven main factors, both internal and external, that are suspected of influencing students' Higher Order Thinking Skills (HOTS) through a questionnaire instrument. These factors include learning interest (7 statement items), learning motivation (5 items), student's intelligence (7 items), physiological condition (8 items), and fatigue (7 items). Additionally, external factors were also measured in depth through the school environment with 19 statement items, as well as the family environment with 15 statement items. Overall, this table illustrates a highly structured and detailed non-test data collection approach to mapping various supporting and inhibiting elements of students' mathematics learning processes.

Table 2. HOTS Mathematics Test Instrument on Ratio and Scale

HOTS Indicator	Description of Items	Item Number
C4 – Differentiating	Students' analyzed the differences in actual distances represented by two maps with different scales.	1
C4 – Organizing	Students' classified maps based on equivalent actual distances.	2
C5 – Checking	Students' examined the correctness of statements regarding actual distances on maps.	3
C5 – Checking	Students' evaluated arguments related to evacuation route distances and travel time.	4
C6 – Planning	Students' designed the most efficient travel plan based on scale, distance, speed, and time allocation.	5

Furthermore, based on Table 2, it is shown that the mathematics test instrument focused on ratio and scale materials and was specifically designed to measure HOTS through five contextual essay questions. The table maps each question to the higher-order cognitive levels of Bloom's Taxonomy, ranging from the C4 to C6 levels. At the analyzing level (C4), there are two questions that require students to differentiate and organize information related to actual distances on scaled maps. At the evaluating levels (C5), two questions are focused on the indicators of checking the correctness of statements and evaluating mathematical arguments. Ultimately, at the creating cognitive level (C6), students are presented with one question to design or plan the most efficient travel route. Overall, this table interprets that the designed test accurately measures students' higher-order thinking skills, from critical analysis to the creation of real-world solutions.

RESULTS

Data obtained from the field were cleaned and transformed into categorical data before being analyzed using Machine Learning with the assistance of the Orange Data Mining application. The dataset consisted of seven factors as features and students' Higher Order Thinking Skills (HOTS) results as the target variable. The data were divided into training data consisting of 391 respondents and testing data consisting of 10 respondents.

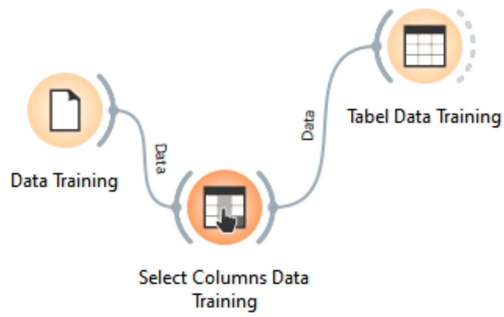

Figure 1. Exploratory Data Analysis (EDA) Display

The distribution of students' mathematical HOTS achievement and the cross-tabulation of its seven influencing factors (learning interest, learning motivation, intelligence, physiological condition, fatigue, school environment, and family environment) across 391 respondents are systematically presented in the following tables.

The exploratory data analysis (EDA) process was carried out using widgets in Orange Data Mining. The File and Data Table widgets were used to import and display the dataset, ensuring it was free from missing values, outliers, and noise. The Select Columns widget was used to define the features and target variables. Feature selection was performed using the Rank widget based on the Chi-Square method to evaluate the statistical significance of each feature toward the target variable. The feature ranking results are presented in Table 3.

Table 3. Students' Family Environment Levels

No.	Factors	Chi-Square Value
1	Phyisilogical Condition	3.124
2	Fatigue	2.526
3	Intelligence	0.744
4	Learning Interest	0.433
5	Family Environment	0.155
6	Learning Motivation	0.016
7	School Environment	0.001

Table 3 shows that physiological condition was the most dominant factor affecting HOTS achievement, followed by fatigue and intelligence. Conversely, school environment and learning motivation yielded the lowest scores. Consequently, learning motivation and school environment were excluded from the classification phase due to their negligible statistical contributions.

Seven supervised machine learning algorithms were implemented and compared using a cross-validation approach. Evaluation metrics encompassing Accuracy, Precision, and Recall are detailed in Table 4.

Table 4. Algorithm Performance Results

Method	Accuracy	Precision	Recall
Naïve Bayes	64%	45%	21%
Random Forest	63%	40%	16%
Decision Tree	61%	38%	23%
kNN	56%	36%	39%
Logistic Regression	64%	40%	9%
SVM	60%	36%	22%
Neural Network	63%	41%	18%

The evaluation indicates that Naïve Bayes and Logistic Regression achieved the highest accuracy of 64%. Furthermore, model performance was evaluated using a Confusion Matrix to provide a detailed assessment of the classification results. The Confusion Matrix was employed to identify the number of correctly and incorrectly classified instances for each class, thereby providing a more comprehensive evaluation of model performance beyond overall accuracy. The results of the Confusion Matrix analysis are presented in Figure 2. and Figure 3.

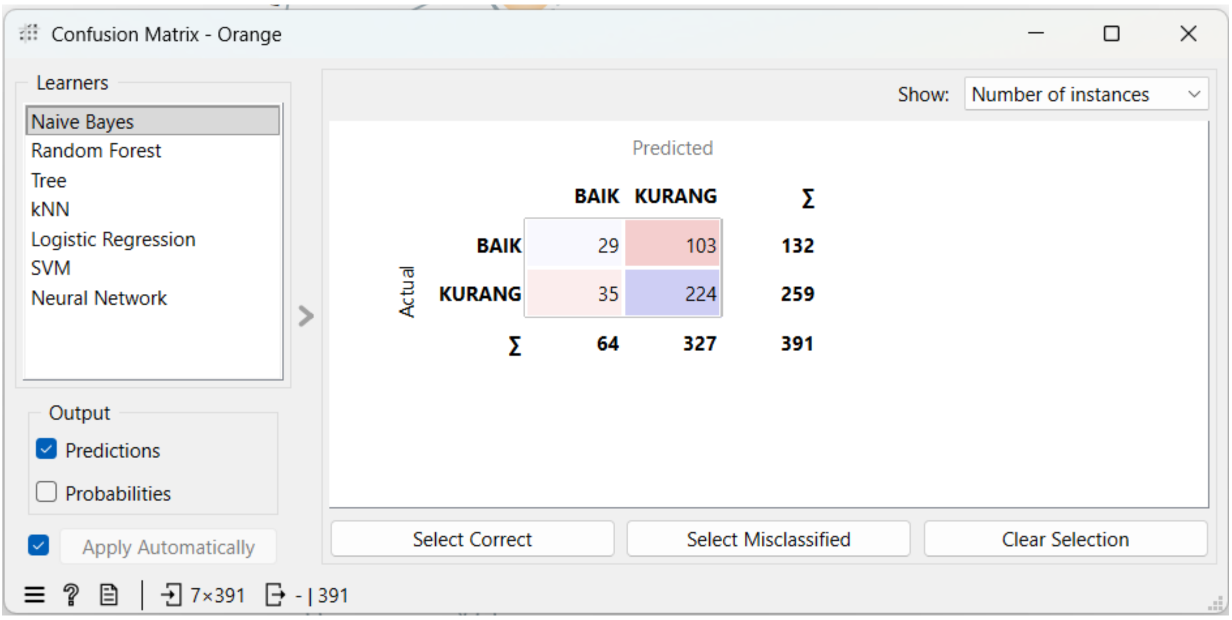

Figure 2. Confusion Matrix of the Naïve Bayes Classification Model

Figure 2. presents the Confusion Matrix of the Naïve Bayes model. The model correctly classified 29 instances in the '*BAIK*' category and 22 instances in the '*KURANG*' category, while 103 instances of '*BAIK*' and 35 instances of '*KURANG*' were misclassified. Based on these results, the model achieved an accuracy of 64%, a precision of 45%, and a recall of 21%.

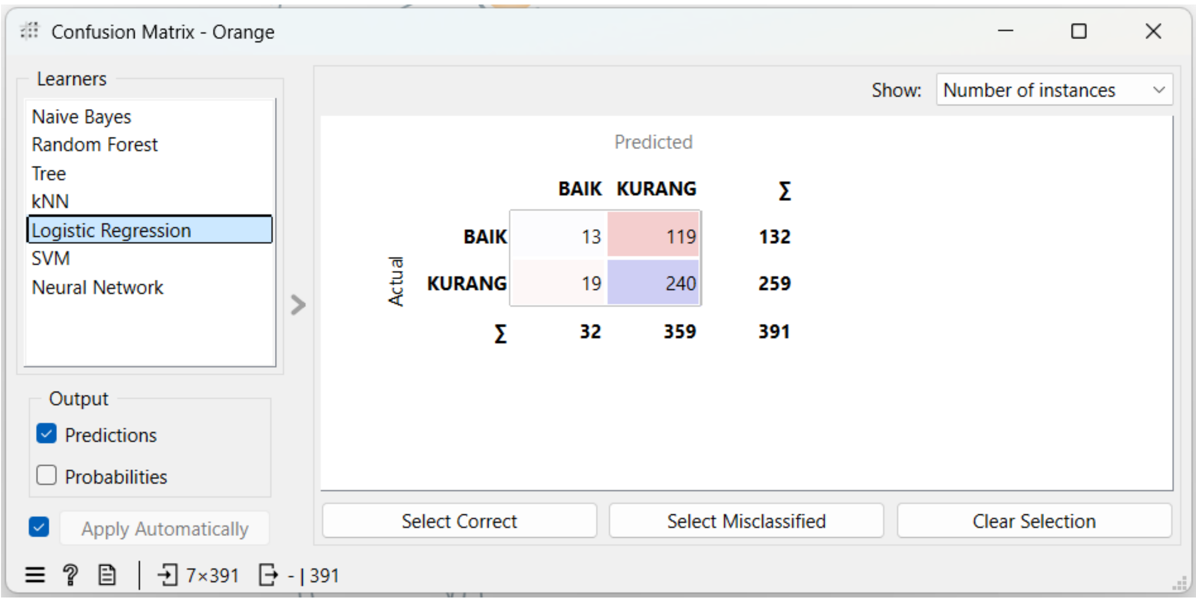

Figure 3. Confusion Matrix of the Logistic Regression Classification Model

Figure 3. presents the Confusion Matrix of the Logistic Regression model. The model correctly classified 13 instances in the '*BAIK*' category and 240 instances in the '*KURANG*' category, while 119 instances of '*BAIK*' and 19 instances of '*KURANG*' were misclassified. The model achieved and accuracy of 64%, a precision of 40%, and a recall of 9%.

Although Naïve Bayes and Logistic Regression achieved the same accuracy of 64%, Naïve Bayes demonstrated better classification performance, as indicated by its higher precision and recall values. Therefore, Naïve Bayes was selected as the best-performing model for classifying students' mathematical HOTS categories in this study.

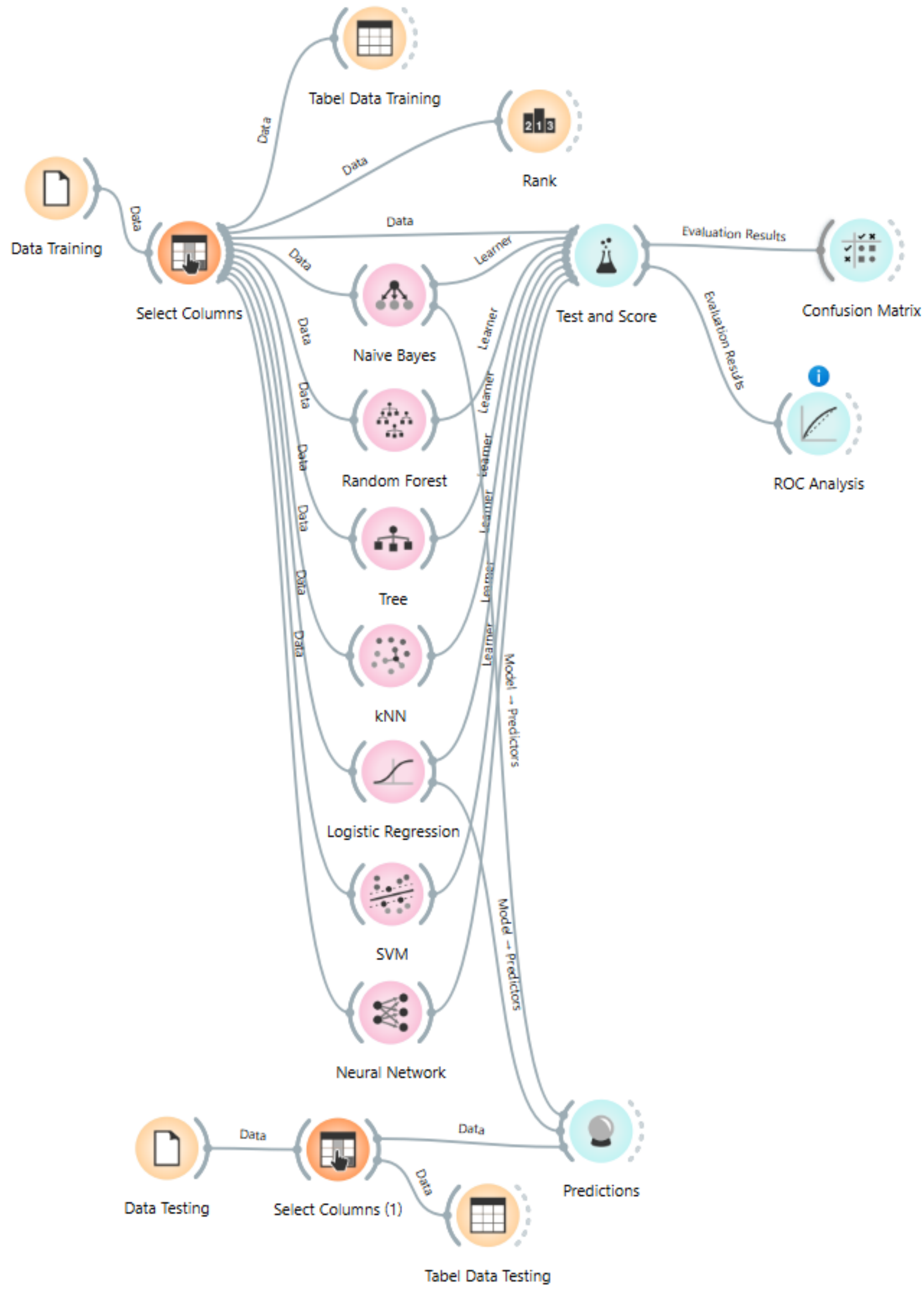

Figure 4. Stages of Data Analysis Process Using Orange

DISCUSSION

The descriptive data analysis clearly reveals a critical educational challenge approximately 66.2% of the junior high school students surveyed possess a '*KURANG*' level of mathematical HOTS. This empirical finding corroborates previous national studies indicating that high-order cognitive processes remain a persistent hurdle for Indonesian students in mathematics education.

A groundbreaking insight discovered through the Chi-Square feature selection process is that non-academic, biological-driven aspects specifically physiological condition (3.124) and fatigue (2.526) exert a much more profound influence on students' high-order thinking abilities than purely cognitive or psychological traits like intelligence (0.744) or learning motivation (0.016). High order thinking tasks, such as analyzing contextual problems and constructing scale models, demand intensive neurological endurance and high cognitive loading. When a student's physiological status is sub-optimal or compromised by acute fatigue, their mental processing capacity shrinks significantly. This mechanism aligns tightly with the foundational theory of Parwati. (2019), which emphasizes that stable physical health directly governs classroom concentration and cognitive absorption rates.

Furthermore, this study provides a unique contribution to the existing literature by challenging conventional educational assumptions. While traditional pedagogical research heavily emphasizes external factors like school environment and teaching facilities as primary drivers of academic success, our Educational Data Mining (EDM) pipeline reveals that the school environment yields the lowest influence (0.001) in determining a student's capacity to complete complex mathematical essay tests. This implies that even within a highly supportive school infrastructure, a student cannot successfully mobilize their higher-order cognitive faculties if they are physically exhausted or sensory deprived. This empirical finding is strongly supported by recent literature indicating that excessive academic burden and mental fatigue, their overall physical and mental health deteriorates, making it nearly impossible to process the complex analytical tasks required for HOTS (Noenoek, 2024).

From a technological standpoint, the integration of test and non-test data via Orange Data Mining successfully proves that machine learning can model complex cognitive outputs with a 64% accuracy rate. The superior performance of the Naïve Bayes algorithm over ensemble methods like Random Forest or complex networks like Neural Networks in this specific context can be attributed to its high resilience when dealing with categorical independent features that possess distinct conditional probabilities. These findings provide an explicit data-driven contribution to modern instructional design, suggesting that schools must transition from merely upgrading educational infrastructure to actively monitoring students' physical well-being, scheduling strategic rest periods, and mitigating physical fatigue to truly foster an environment where mathematical high-order thinking can thrive.

CONCLUSION

Based on the results of this research, the implementation of machine learning using Orange Data Mining was effective in identifying the dominant factors influencing students' mathematical

Higher Order Thinking Skills (HOTS) through data preprocessing, Chi-Square feature selection, classification modeling, and model evaluation.

The essence of these findings provides a fresh perspective in educational discussion physiological condition and fatigue were revealed as the most dominant factors affecting students' HOTS, surpassing traditional cognitive and psychological factors such as intelligence, learning interest, and family environment. Furthermore, the Naïve Bayes algorithm proved to be the most optimal and consistent model for predicting these mathematical outcomes, providing a valuable probabilistic framework for instructional design.

However, this study is subject to certain limitations. The predictive modeling and feature exploration were inherently bounded by the pre-defined non-test instruments and the specific categorical scope used during the data mining process. Additionally, the empirical validation was focused on a selected group of junior high school participants and specific mathematical contexts, which may limit immediate generalization.

Based on these findings, several recommendations can be proposed. Students are expected to maintain good physiological conditions and reduce fatigue during learning, while teachers and schools should utilize these insights to design supportive learning strategies and educational programs. Educators and policymakers must adopt a more comprehensive perspective that balances academic responsibilities with students' physical and mental health. Implementing adaptive teachine practices, minimizing unnecessary repetitions, and ensuring adequate rest from academic burdens are crucial steps to improve high-order academic achievements. Finally, future researchers are recommended to expand on these limitations by developing similar studies using other machine learning methods or software, investigating additional hidden factors, and conducting research on different mathematical topics with broader participant groups to obtain more comprehensive findings.

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