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Research Article

STUDENT GRADUATION PREDICTION USING DECISION TREE ALGORITHM WITH CRISP-DM METHOD (CASE STUDY: ITB AHMAD DAHLAN)

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Abstract

On-time graduation is an important indicator of higher education effectiveness; however, delays in student graduation are still observed at ITB Ahmad Dahlan Jakarta. This study develops a student graduation prediction system using the Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology and the Decision Tree algorithm based on historical academic data. The model was built through six CRISP-DM stages, including problem understanding, data preparation, modeling, and evaluation. Testing results indicate high performance with an Accuracy of 97.44%, Precision of 97.14%, Recall of 100%, and F1-Score of 98.55%. This system has the potential to support strategic decision-making to enhance academic quality through data-driven approaches.

Keywords: Academic Data, CRISP-DM, Decision Tree, Delayed Study, Student Graduation

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INTRODUCTION

Student academic success is one of the main indicators of the quality of higher education and has always been a serious concern for universities (de Andrés-Sánchez et al., 2024). One parameter of academic success is on-time graduation, which not only reflects individual student achievement but also demonstrates the quality of academic governance within the institution (Fitriyah et al., 2020).

Problems arise when on-time graduation rates fall below expectations (Kar et al., 2024), as this can lead to increased educational costs, delays in students' professional careers, and a decline in the institution's reputation and accreditation (Supangat & Sulistyawan, 2023). These conditions demand data-driven strategies capable of predicting the risk of delayed graduation early on, enabling timely and measurable academic interventions.

With technological advancements, machine learning has increasingly become a widely adopted approach in the education sector to predict student academic success (Sheikhkhoshkar et al., 2025). Previous studies have shown that predictive methods can help institutions identify students at risk of delayed graduation based on academic data such as GPA, the number of credits taken, and the frequency of course retakes (Mukhsinah et al., 2024). For example, Wijaya et al. successfully integrated the CRISP-DM methodology with the Naïve Bayes algorithm to predict on-time graduation, achieving an accuracy rate of 86.38%. Another study by Amri et al. (Wijaya, 2020) employed the K-Nearest Neighbor (K-NN) algorithm with an accuracy of 96.95%, while Darmawan et al. demonstrated that Support Vector Machine (SVM) and Random Forest (RF) algorithms could achieve prediction accuracy rates exceeding 98% (Darmawan et al., 2023). These findings highlight the significant potential of machine learning to enhance academic efficiency and accountability in higher education institutions.

However, at Ahmad Dahlan Institute of Technology and Business (ITB Ahmad Dahlan) Jakarta, the application of machine learning for predicting student graduation rates remains very limited (Castro et al., 2025). Based on PDDIKTI data (2024), the on-time graduation rate for the Information Technology program was only 42.38% out of 446 students, while the Business program recorded a rate of just 12.31% out of 1,186 students. These figures reveal a serious problem that could affect graduate quality, institutional accreditation, and educational management effectiveness (Du & Zhu, 2025). To date, no studies have specifically integrated the CRISP-DM methodology with the Decision Tree algorithm in the context of ITB Ahmad Dahlan Jakarta, even though both approaches have complementary strengths (Rishabh & Das, 2025). CRISP-DM provides a systematic data analysis framework from business understanding and data preparation to modeling and evaluation (Bokrantz et al., 2023), while Decision Tree is widely recognized for producing predictive models that are not only accurate but also easy for academic stakeholders to interpret (Villar & de Andrade, 2024).

Based on this situation, the present study focuses on developing a student graduation prediction system using the Decision Tree algorithm combined with the CRISP-DM methodology at ITB Ahmad Dahlan Jakarta (Taleb, 2025). The research aims to not only predict students at risk of delayed graduation with high accuracy but also provide actionable insights for academic counseling programs (Hamid & Roy, 2025), curriculum planning, and overall educational quality improvement strategie (Li et al., 2024). With a structured, data-driven prediction system, universities can implement more targeted and effective preventive measures (Mariyam et al., 2025), thereby increasing on-time graduation rates while maintaining institutional reputation amid the growing challenges of global competition.

RESEARCH METHOD

This study employs the CRISP-DM (Cross-Industry Standard Process for Data Mining) framework to develop a student graduation prediction mode (Wang & Zhou, 2025). This approach was selected because it provides a systematic process encompassing problem understanding, data collection and preparation, modeling, evaluation, and model implementation (Bokrantz et al., 2023).

Research Design

The research was conducted at ITB Ahmad Dahlan Jakarta using academic data from the 2019-2021 student cohorts. The entire research process, including data collection, modeling, and preparation of the final report, took place from March to August 2025.

This study uses a quantitative approach with the CRISP-DM methodology as the main framework (Khan et al., 2024). The research focuses on developing a student graduation prediction model using the Decision Tree algorithm, evaluating model accuracy, and identifying the factors influencing delayed graduation.

Research Target/Subject

The research population consists of 625 students with academic variables including Total credits earned, Final GPA, Study duration, Graduation statu (Rafiq et al., 2025). ampling followed the purposive sampling technique to ensure relevant variables were included in the analysis.

Research Procedure

The research procedure in this study follows the CRISP-DM phases to ensure a structured and systematic approach. The process begins with the business understanding phase, which involves identifying the problem of delayed graduation and its implications for universities. This is followed by the data understanding phase, where academic data is reviewed to identify patterns related to student performance. In the data preparation phase, categorical data is encoded, numerical data is normalized, and the dataset is divided into training and testing sets using an 80:20 ratio. The modeling phase involves applying the Decision Tree algorithm and optimizing its parameters to improve accuracy. Subsequently, the evaluation phase is conducted to assess model performance using metrics such as accuracy, precision, recall, F1-score, and the confusion matrix. Finally, the deployment phase prepares the model for potential implementation in detecting the risk of delayed graduation at an early stage.

Instruments, and Data Collection Techniques

Data collection in this study was conducted using three complementary methods to ensure comprehensive and reliable data (Liu et al., 2024). Observation was carried out by collecting academic records from the university information system to obtain relevant student performance data. In addition, interviews were conducted through discussions with academic staff to gain insights into factors affecting graduation rates. Furthermore, documentation techniques were used by analyzing academic transcripts, GPA records, semester GPA reports, and academic regulations to support and validate the findings.

Data Analysis Technique

Data analysis in this study was conducted quantitatively using the Decision Tree algorithm (Aregbeshola & Adekunle, 2024) to classify and predict student graduation outcomes. The performance of the model was evaluated using several metrics, including accuracy to measure overall correctness, precision to assess the proportion of correctly predicted positive cases, recall to evaluate the model's ability to identify actual positive cases, and F1-score to provide a balanced measure between precision and recall. In addition, a confusion matrix was used to present a detailed comparison between predicted and actual classifications, allowing for a clearer understanding of the model's performance.

RESULTS AND DISCUSSION

The discussion is focused on connecting data and analysis results with the problem or research objectives and the wider theoretical context (Aytekin, 2025). Could this discussion be the answer to the question why these facts were found in the data?

A written discussion is attached to the data discussed (Yücesan, 2025). The discussion is inseparable from the data discussed, as well as conveying the novelty in this research and its implications.

This study not only focuses on presenting raw data but also on how the data are processed, analyzed, and interpreted to address the research questions (Susila et al., 2024). Therefore, the results and discussion section provides a comprehensive explanation, starting from the initial computation process, the construction of the decision tree as the primary analysis method, to the model evaluation stage for measuring the accuracy and reliability of the findings obtained.

Modeling and Initial Computation

The student graduation classification model was developed using the Decision Tree (C5.0) algorithm with the parameters shown in Table 1 below.

Table 1. Model Parameters

Parameter	Value	Description
Algorithm	Decision Tree	Decision tree classification
Criterion	Entropy	Measures Information Gain
Max Depth	5	Prevents overfitting
Training Size	80%	Data used to train the model
Test Size	20%	Data used to evaluate the model

The dataset consists of 500 student graduation records from ITB Ahmad Dahlan Jakarta, divided into 80% training data (400 records) and 20% testing data (100 records). The data classification details are as follows: 452 students graduated on time and 48 students graduated late

Total Entropy Calculation

$$Entropy = -\sum p_i \log_2(p_i)$$

(1)

With:

Total data $S = 500$

On-time graduation = 452

Late graduation = 48

$$Entropy\ Total = -\left(\frac{452}{500}\log_2\frac{452}{500}\right) - \left(\frac{48}{500}\log_2\frac{48}{500}\right) = 0{,}4562$$

(2)

Main Attribute Calculation

GPA Semester 1

- $S_{\geq 3,5} = 299 \rightarrow On - time = 271. Late = 28 \rightarrow Entropy = 0.460$
- $S_{\geq 3,5} = 201 \rightarrow On - time = 181. Late = 20 \rightarrow Entropy = 0.469$

Information Gain

$$IG = 0{,}4562 - \left(\frac{299}{500} \times 0{,}460 + \frac{201}{500 \times 0{,}469}\right) = 0{,}00007$$

(3)
Gain Ratio

$$GR = \frac{IG}{Split\ Info} = \frac{0{,}00007}{0{,}9721} = 0{,}00007$$

(4)
Credits Semester 1

- $S_{\geq 19} = 20 \rightarrow On - time = 18, Late = 2 \rightarrow Entropy = 0{,}4690$
- $S_{<19} = 480 \rightarrow On - time = 434, Late = 46 \rightarrow Entropy = 0{,}4097$

Confusion Matrix Gain

$$IG = 0{,}4562 - \left(\frac{20}{500} \times 0{,}4690 + \frac{480}{500} \times 0{,}4097\right) = 0{,}0451$$

(5)
Gain Ratio:

$$GR = \frac{0{,}0451}{0{,}2423} = 0{,}1862$$

(6)
Further Calculations

Calculation Results for Other Attributes:

Table 2. Further Calculations

Attribute	Info *Gain*	*Split Info*	*Gain Ratio*
GPA Semester 2	-0,083	0,862	-0,096
GPA Semester 3	-0,038	0,738	-0,051
GPA Semester 4	-0,038	0,867	-0,044
GPA Semester 5	-0,061	0,867	-0,070
GPA Semester 6	-0,034	0,941	-0,036
Credits Semester 2	0,011	0,835	0,013
Credits Semester 3	0,000	0,000	-
Credits Semester 4	0,012	0,899	0,013
Credits Semester 5	0,010	0,880	0,011
Credits Semester 6	0,005	0,920	0,005

This result identifies the attribute with the highest Gain Ratio to serve as the root node in the decision tree.

Decision Tree

Based on calculations using the Decision Tree (C5.0) algorithm, a decision tree was generated to map the key factors influencing student graduation (Rawat et al., 2025). The model was built from semester GPA data, which helps predict whether students will graduate on time or late.

1) Root Node: GPA Semester 4
   The GPA for Semester 4 has the highest Gain Ratio of 0.0308, making it the root node.

- GPA ≥ 3.5 → the majority of students graduate on time.
- GPA < 3.5 → other factors, such as Semester 1 GPA, need to be considered.

2) Branch: GPA Semester 4 < 3.5 → Semester 1
GPA Gain Ratio = 0.0236.

- GPA ≥ 3.5 → there is still a chance to graduate on time.
- GPA < 3.5 → the risk of late graduation increases.

3) Branch: Semester 1 GPA < 3.5 → Semester 6 GPA
Gain Ratio = 0.1338.

- GPA ≥ 3.5 → there is an opportunity to catch up.
- GPA < 3.5 → almost certain to graduate late.

4) Branch: Semester 6 GPA < 3.5 → Semester 3 & 5 GPA Gain Ratio = 0.1374.

- Low GPA in both semesters → majority graduate late.
- GPA ≥ 3.5 in either semester → small chance of on-time graduation.

Model Evaluation Results

Testing was conducted using 125 test data records. Table 2 below shows the resulting prediction distribution.

Table 3. Prediction Distribution

Category	Abbreviation	Count	Description
True Positive	TP	92	Students who graduated on time and were correctly predicted
True Negative	TN	3	Students who graduated late and were correctly predicted
False Positive	FP	5	Students who graduated late but were predicted on time
False Negative	FN	25	Students who graduated on time but were predicted late

-

Accuracy

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

(7)

$$Akurasi = \frac{92 + 3}{32 + 3 + 5 + 25} = \frac{95}{125} = 0.76\ (76\%)$$

(8)

Precision

$$Precision = \frac{TP}{TP + FP}$$

(9)

$$Precision = \frac{34}{34 + 1} = 0{,}9714\ (97{,}14\%)$$

(10)

Recall

$$Recall = \frac{TP}{TP + FN}$$

(11)

$$Recall = \frac{92}{92 + 25} = 0{,}7863\ (78{,}63\%)$$

(12)

F1-Score

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

(13)

$$F1 = 2 \times \frac{0{,}9484 \times 0{,}7863}{0{,}9484 \times 0{,}7863} = 0{,}86\ (86\%)$$

(14)

Evaluation Metrics Table

Table 4. Evaluation Metrics

Metrik	Nilai
Accuracy	76,00%
Precision	94,84%
Recall	78,63%
F1-Score	86,00%

System Implementation

The implementation phase was carried out to ensure that the designed system operates according to specifications in a real environment (Pan, 2024). Each system page serves specific functions, ranging from data management to student graduation prediction.

Admin Login Page

The initial page allows users to access the system using a username and password. Data security is verified at this stage.

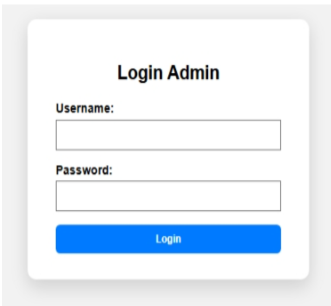
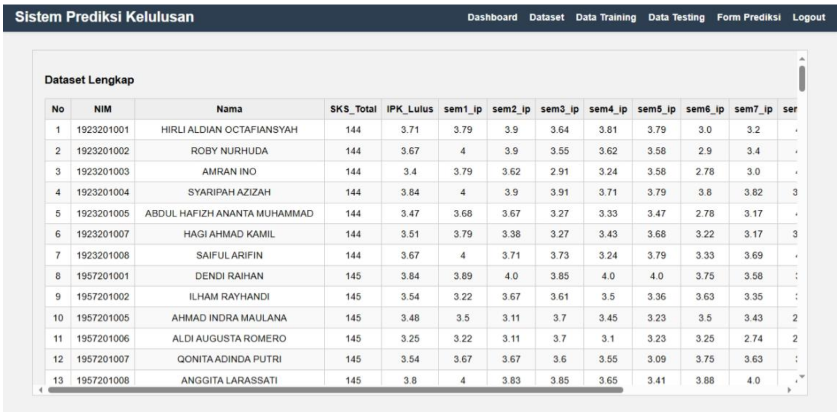


Figure 1. Admin Login Page

Figure 1 shows the Admin Login Page of the system, which provides a secure entry point for administrators to access the application. This interface typically includes input fields for username and password, along with a login button to authenticate user credentials. It ensures that only authorized administrators can access system features and manage operational data securely.

Dashboard Page

It contains a form for uploading datasets in CSV format from the academic staff of ITB Ahmad Dahlan Jakarta.



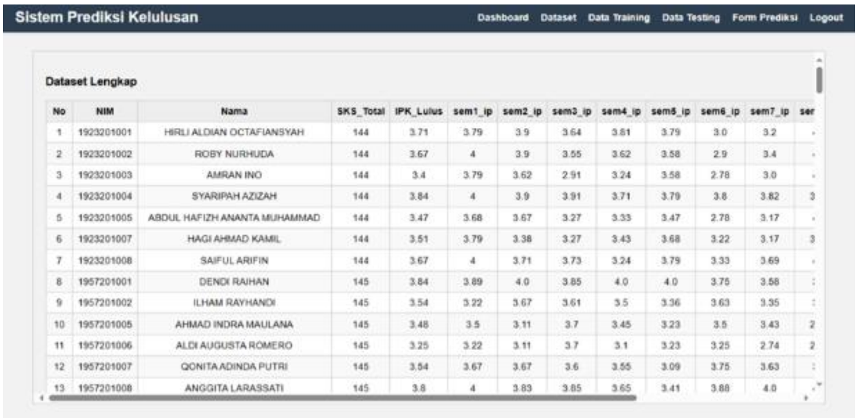
No	NIM	Nama	SKS_Total	IPK_Lulus	sem1_ip	sem2_ip	sem3_ip	sem4_ip	sem5_ip	sem6_ip	sem7_ip
1	1923201001	HIRLI ALDIAN OCTAFIANSYAH	144	3.71	3.79	3.9	3.64	3.81	3.79	3.0	3.2
2	1923201002	ROBY NURHUDA	144	3.67	4	3.9	3.55	3.62	3.58	2.9	3.4
3	1923201003	AMRAN INO	144	3.4	3.79	3.62	2.91	3.24	3.58	2.78	3.0
4	1923201004	SYARIPAH AZIZAH	144	3.84	4	3.9	3.91	3.71	3.79	3.8	3.82
5	1923201005	ABDUL HAFIZH ANANTA MUHAMMAD	144	3.47	3.68	3.67	3.27	3.33	3.47	2.78	3.17
6	1923201007	HAGI AHMAD KAMIL	144	3.51	3.79	3.38	3.27	3.43	3.68	3.22	3.17
7	1923201008	SAIFUL ARIFIN	144	3.67	4	3.71	3.73	3.24	3.79	3.33	3.69
8	1957201001	DENDI RAIHAN	145	3.84	3.89	4.0	3.85	4.0	4.0	3.75	3.58
9	1957201002	ILHAM RAYHANDI	145	3.54	3.22	3.67	3.61	3.5	3.36	3.63	3.35
10	1957201005	AHMAD INDRA MAULANA	145	3.48	3.5	3.11	3.7	3.45	3.23	3.5	3.43
11	1957201006	ALDI AUGUSTA ROMERO	145	3.25	3.22	3.11	3.7	3.1	3.23	3.25	2.74
12	1957201007	QONITA ADINDA PUTRI	145	3.54	3.67	3.67	3.6	3.55	3.09	3.75	3.63
13	1957201008	ANGGITA LARASSATI	145	3.8	4	3.83	3.85	3.65	3.41	3.88	4.0

Figure 2. Dashboard Page

Figure 2 presents the Dashboard Page of the system, which serves as the main interface displaying an overview of key information and system activities. This page typically includes summaries such as user statistics, transaction data, and system notifications, along with quick access to main features. It enables users to monitor performance and navigate the system efficiently.

Dataset Page

Displays the raw dataset containing student data before the training and testing data split is performed.



No	NIM	Nama	SKS_Total	IPK_Lulus	sem1_ip	sem2_ip	sem3_ip	sem4_ip	sem5_ip	sem6_ip	sem7_ip
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2	1923201002	ROBY NURHUDA	144	3.67	4	3.9	3.55	3.62	3.58	2.9	3.4
3	1923201003	AMRAN INO	144	3.4	3.79	3.62	2.91	3.24	3.58	2.78	3.0
4	1923201004	SYARIPAH AZIZAH	144	3.84	4	3.9	3.91	3.71	3.79	3.8	3.82
5	1923201005	ABDUL HAFIZH ANANTA MUHAMMAD	144	3.47	3.68	3.67	3.27	3.33	3.47	2.78	3.17
6	1923201007	HAGI AHMAD KAMIL	144	3.51	3.79	3.38	3.27	3.43	3.68	3.22	3.17
7	1923201008	SAIFUL ARIFIN	144	3.67	4	3.71	3.73	3.24	3.79	3.33	3.69
8	1957201001	DENDI RAIHAN	145	3.84	3.89	4.0	3.85	4.0	4.0	3.75	3.58
9	1957201002	ILHAM RAYHANDI	145	3.54	3.22	3.67	3.61	3.5	3.36	3.63	3.35
10	1957201005	AHMAD INDRA MAULANA	145	3.48	3.5	3.11	3.7	3.45	3.23	3.5	3.43
11	1957201006	ALDI AUGUSTA ROMERO	145	3.25	3.22	3.11	3.7	3.1	3.23	3.25	2.74
12	1957201007	QONITA ADINDA PUTRI	145	3.54	3.67	3.67	3.6	3.55	3.09	3.75	3.63
13	1957201008	ANGGITA LARASSATI	145	3.8	4	3.83	3.85	3.65	3.41	3.88	4.0

Figure 3. Dataset Page

Figure 3 presents the Dataset Page of the system, which displays the collection of data used for analysis and modeling. This page typically includes structured tables containing student records, attributes, and relevant variables required for the Decision Tree process. It allows users to view, manage, and prepare data efficiently before proceeding to the modeling stage.

Data Training Page

Contains 80% of the training data used to build the Decision Tree using the C5.0 algorithm.

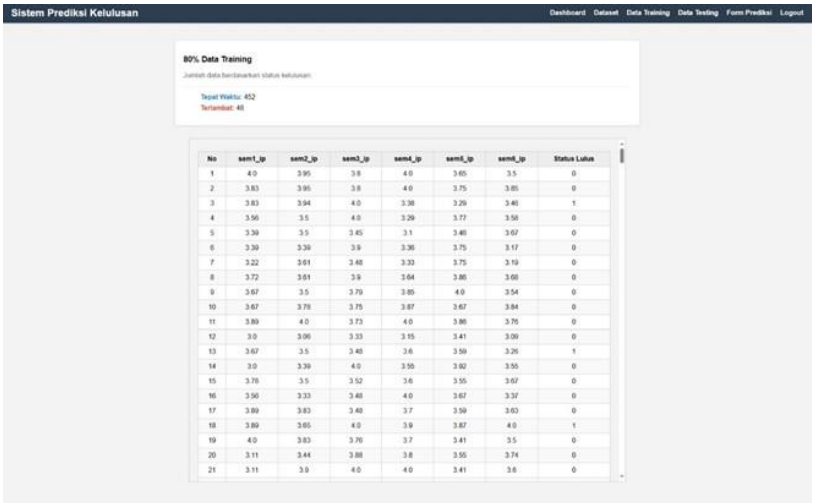

Figure 4. Data Training Page

Figure 4 presents the Data Training Page of the system, which is used to process and train the dataset using the selected algorithm. This page typically displays the training data, parameter settings, and the execution of the training process, allowing users to build the Decision Tree model. It supports effective model development by preparing the system to learn patterns from the data.

Data Testing Page

Displays 20% of the test data to measure the model's accuracy using the Confusion Matrix and Accuracy value.

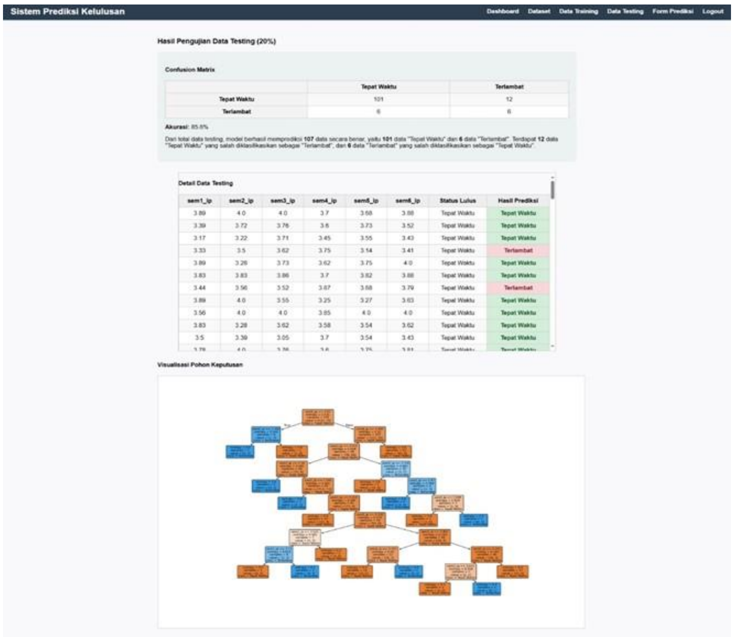

Figure 5. Data Testing Page

Figure 5 presents the Data Testing Page of the system, which is used to evaluate the trained model using testing data. This page typically displays the test dataset along with prediction results, allowing users to compare actual and predicted outcomes. It supports model validation by providing insights into the performance and accuracy of the Decision Tree model.

Prediction Form Page

A form for manually inputting semester GPA values to predict a student's graduation status.

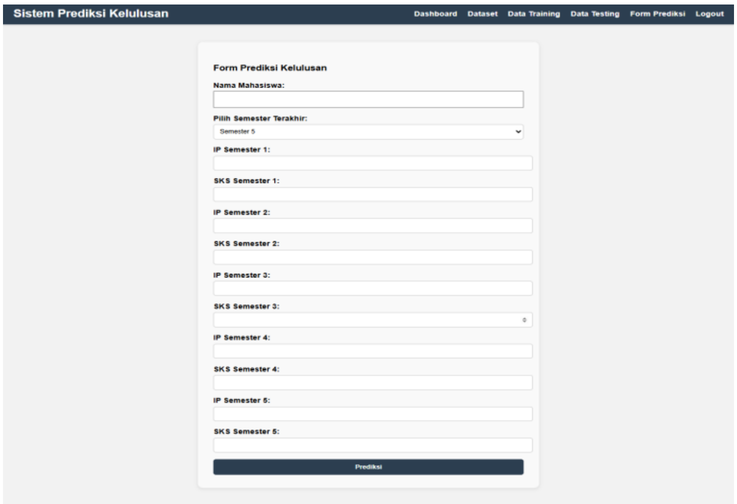

Figure 6. Prediction Form Page

Figure 6 presents the Prediction Form Page of the system, which allows users to input relevant data for generating predictions. This page typically includes fields for entering variables related to student performance, enabling the system to process the input using the trained Decision Tree model. It supports decision-making by providing quick and accurate prediction results based on user input.

Prediction Results Page

Displays the prediction results based on the data entered through the previous form.

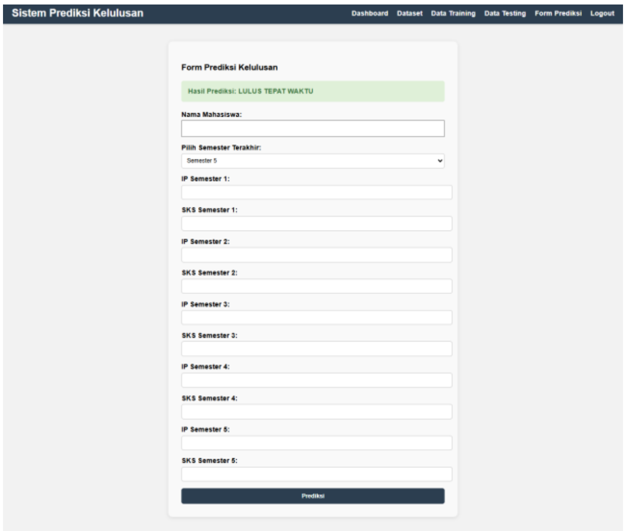

Figure 7. Prediction Results Page

Figure 7 presents the Prediction Results Page of the system, which displays the output generated from the prediction process. This page typically shows the predicted classification along with supporting information such as probability or confidence level, allowing users to interpret the results clearly. It helps users make informed decisions by presenting the outcome of the Decision Tree model in an understandable format.

Decision Tree

Decision Tree visualization from both manual calculations and Python-based computations. The manual version is limited to two GPA criteria (<3.5 and ≥3.5).

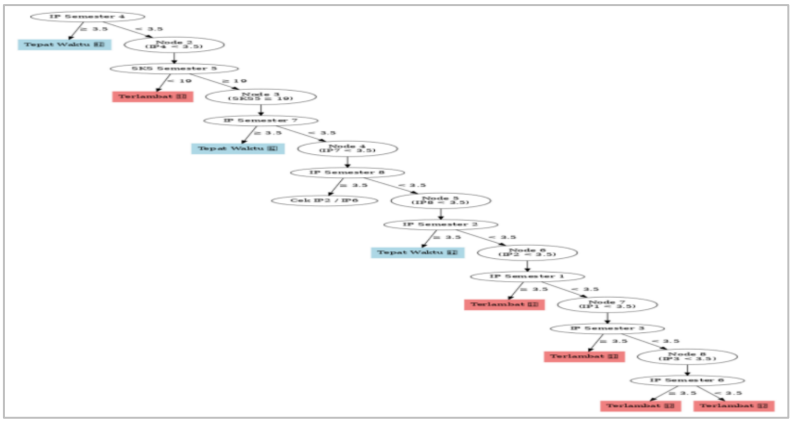

Figure 8. Manual Decision Tree

Figure 8 presents the Manual Decision Tree, which illustrates the step-by-step structure of decision-making based on predefined rules. This diagram shows how input variables are evaluated through a series of nodes and branches until a final classification is reached. It helps users understand the logic behind the model by visualizing how decisions are formed from the dataset.

CONCLUSION

Based on the implementation and testing results, the CRISP-DM methodology was successfully applied in the systematic development of a student graduation prediction system using Decision Tree, providing a structured and efficient framework. The Decision Tree model demonstrated satisfactory performance with an Accuracy of 76.00%, Precision of 94.84%, Recall of 78.63%, and F1-score of 86.00%, although there remains potential for improvement, particularly in Recall, to identify more students graduating on time. Factors such as GPA, total credits, employment status during study, and the frequency of course retakes were found to influence delayed graduation. Evaluation also indicated that the system can classify data with reasonable accuracy, yet further development, such as adding variables or employing alternative algorithms, is needed to enhance model performance.

AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.
Author 2: Conceptualization; Data curation; In-vestigation.
Author 3: Data curation; Investigation.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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