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A Machine Learning Approach to Predicting On-Time Graduation in Indonesian Higher Education

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Abstract

Graduating on schedule is a critical milestone for students in higher education, serving as a key indicator of both institutional effectiveness and student success. This study uses machine learning techniques to predict on-time graduation in Indonesian higher education. A dataset comprising 133 students from an engineering department over four academic years (2019–2023) was analyzed using the CRISP-DM framework. The research employed nine machine learning models, including Random Forest, Logistic Regression, Neural Networks, etc., to identify key predictors of on-time graduation. The result showed that Random Forest outperformed other models by achieving an accuracy of 85% and an AUC of 0.875. Additionally, the study developed a learning analytics dashboard to visualize predictive insights, offering actionable data for educators and administrators. The system's performance was evaluated based on functionality, usability, efficiency, and reliability as the key intersecting factors from ISO/IEC 25010 and WebQEM frameworks, validating its quality and relevance for practical educational use. The result demonstrated high functionality, efficiency, and reliability, and positive usability feedback was received from both students and educators. The findings highlight the top ten important factors, such as cumulative GPA (CGPA), extracurricular involvement, programming, and social science courses, that predict on-time graduation, providing valuable insights for enhancing student outcomes in Indonesian higher education.

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INTRODUCTION

Understanding the factors influencing on-time graduation is crucial for educational institutions to enhance support mechanisms and optimize student outcomes. Timely completion of a degree program not only reflects the effectiveness of an educational institution in running its process but also significantly impacts students' academic and career trajectories [1], [2], [3]. On-time graduation has been linked to better employment prospects, higher earning potential, and better overall life satisfaction [4], [5]. Conversely, delays in graduation can lead to increased financial burdens, extended time in education, and more likely potential disengagement from academic goals [6], [7]. Given these challenges, a data-driven approach, such as machine learning, can play a crucial role in predicting and identifying students at risk of delayed graduation, allowing institutions to implement timely, targeted interventions that support student success.

The educational situation in Indonesia has undergone significant changes and challenges. Despite efforts to improve access to higher education, the country continues to face issues related to the quality of education and graduation timeliness [8], [9]. One of the critical issues is the prolonged time students take to graduate, which can be attributed to various factors such as curriculum design, student engagement, and institutional support systems. Regarding the educational context in Indonesia, writing a thesis for undergraduate students is a compulsory course which every student should pass to graduate. According to Diasti and Mbato [10], students who complete their degrees within four years are considered on-time graduates, whereas those who take longer may face additional challenges in maintaining motivation and engagement. Kementrian Pendidikan dan Kebudayaan (Ministry of Education and Culture) reported that the average on-time graduation rate from three top universities in Indonesia in the last five years was 38.43% [11]. In recent years, the government has implemented several policies to address these issues, such as the "Merdeka Belajar" (Freedom to Learn) policy, aimed at providing more flexible learning pathways [12]. Through this policy, students can earn credits not only from courses but also through work or internships, allowing them to fulfill graduation requirements while gaining practical experience. However, there is still a considerable gap in utilizing data-driven approaches to enhance educational outcomes [13].

This study focuses on machine learning analysis that integrates various features of students' demographic information and academic performance to predict on-time graduation. Machine learning's ability to uncover complex patterns and trends makes it more effective than traditional statistical methods for predictive analysis in Educational Data Mining. It enables models that identify at-risk students in complex datasets to support timely graduation [14]. This research explores the efficacy of machine learning algorithms in predicting students' likelihood of graduating on time based on demographic and academic performance data. The motivation behind this study arises from the importance of developing a system that can be utilized proactively for identifying students at risk of not graduating on time by stakeholders in education such as educators, school administrators, students, and even parents. By leveraging machine learning techniques, this research aims to address key research questions that can resolve on the underlying factors influencing on-time graduation and contribute to the development of targeted interventions to support student success.

This study also focuses on the context of higher education in Indonesia, where there may be unique socio-cultural and institutional factors at play, the need to identify and address barriers to on-time graduation is particularly crucial [15], [16]. Understanding the demographic characteristics associated with on-time graduation is essential for identifying vulnerable student populations and adjusting support mechanisms accordingly [17]. By examining factors such as age, gender, socioeconomic background, and geographic location [15], this research aims to elaborate on the demographic determinants of on-time graduation in the Indonesian higher education context. Besides demographic factors, the main factor of academic performance also plays a pivotal role in students' progression toward timely completion of their degree programs [18]. By analyzing academic indicators such as GPAs, course scores, and performance in key subjects, this research assesses the relationship between academic performance metrics and on-time graduation outcomes [19], [20].

The insights gained from this study have the potential to inform educational policies and interventions [21] adapted to the Indonesian higher education settings. By identifying the demographic factors and academic performance metrics associated with on-time graduation, educational institutions can implement targeted support programs aimed at mitigating barriers to timely completion. Furthermore, the development of predictive models and warning system mechanisms can enable early identification of students at risk of delayed graduation or even dropout early diagnosis, allowing for timely interventions to support their academic progress and success [22].The background and motivation of this research attempt to advance our understanding of the factors influencing on-time graduation in Indonesian higher education institutions particularly and contribute to the development of data-driven strategies to enhance student outcomes generally.

This study explores two primary areas: educational data mining and system development. It seeks to identify the key factors influencing on-time graduation in Indonesian higher education, examining

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how these factors vary across different student demographics. Additionally, it evaluates the accuracy and effectiveness of predictive models used to forecast timely graduation. On the system development side, the study assesses the performance of the developed system using standard software assessment criteria and investigates how students and educators perceive and interact with the system.

Table 1. Students Demographic Attributes

Attribute ID	Value	Description
Status	Active, Graduate, Leave, Drop	Students' current status when the data was collected
Study_Program	Education in Electronics Engineering (Edu_Elect) Education in Informatics Engineering (Edu_Info) Information Technology (IT)	-
School_Type	Public, Private	Students' high school type
School_Major	Science, Social Science, EEC (Electrical, Electronical, and Computer related), Non-EEC	Students' major in high school. EEC and Non-EEC are major in vocational school
Student_Type	Regular, Non-Regular	Regular is a student type for those who are accepted via national admission channels
Gender	Male, Female	-
Age		Students' age in the admission period
Domicile	Yes, No	Yes = students living with family No = students living outside the family house
Admission_Channel	SNMPTN, SBMPTN, SM	SNMPTN is a national university admission and is held earliest in the calendar where it uses high school academic reports. SBMPTN is a national university admission Examination. SM is admission held by a related school. Every school has this admission.
Funding_Type	Funded, Subsidized, Private	Acceptance of national admission received subsidy by default. Private funding is designed for school-owned admission, with the exception of students from low-income families.
F_Income, M_Income	IDR 0 - IDR 501.000 IDR 501.000–IDR 1.000.000 IDR 1.001.000- IDR 1.500.000 IDR 1.501.000-IDR 2.000.000 IDR 2.001.000-IDR 2.500.000 IDR 2.501.000-IDR 3.000.000 IDR 3.001.000-IDR 3.500.000 IDR 3.501.000-IDR 4.000.000 >IDR 4.000.000	Student's Father's (and Mother's) income per month
F_Edu, M_Edu	No School, Elementary School, Junior High School, Senior High School, Diploma, Bachelor, Master, Doctor	Student's Father's (and Mother's) last education degree
F_Job, M_Job	Government Worker, Seller, Freelancer, Entrepreneur, Labor, Farmer, Deceived, etc.	Student's Father's (and Mother's) main occupation

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METHODS

This study employs a mixed-method approach, integrating both quantitative and qualitative research. It is structured in two phases: the first phase involves conducting Educational Data Mining (EDM) and machine learning modelling to analyze factors influencing on-time graduation. The second phase focuses on developing a website-based system for visualizing data insights and predicting on-time graduation, followed by WebQEM (Web Quality Evaluation Method) assessment and an analysis of system perceptions from educators and students. This study used a dataset from the Department of Education in Electronics and Informatics Engineering at a public university in Yogyakarta, Indonesia, covering the academic years from 2019/2020 to 2022/2023. The dataset, sourced from the academic information system, initially included 539 student records from the 2019 intake. However, only 133 records contained both demographic and academic performance data. The remaining records had missing information, such as demographic details or student scores, and were removed during data cleaning. While this reduced the dataset's size, it still allowed for meaningful analysis, though with some limitations in statistical power. The final dataset includes 52 features: 51 independent variables and one target feature.

Research Variables

In this study, we used the primary data collected from a few academic information systems. The independent and dependent variables are drawn and concluded from students' information from the system. In the context of this research, which is educational data mining and further using supervised learning algorithms, independent variables will serve as features (X), and the dependent variables will serve as target (y), where features (X) influence and contribute to the target (y) outcome.

The independent variables are represented by selected features from the dataset, which include students' demographic information as described in Table 1 and learning performance as described in Table 2. The dataset features 26 demographic variables in total. Learning performance varies by study program: Education in Electronics Engineering includes 70 mandatory courses; Education in Informatics Engineering includes 92 courses with 31 electives; and Information Technology includes 101 courses with 36 electives.

Table 2. Students Academic Attributes

Attribute ID	Value	Description
National_exam	1.00 – 10.00	Students' average score from high school national exam.
Toefl	310 - 677	TOEFL ITP CBT (Computer-based Test)
Extra_curr	Yes, No	Students' extra-curricular
achievement	None, National, International	Students' achievement during the undergraduate period
Course_score	0 – 4.00	All courses taken by students in 4 years. This attribute is the largest attribute in the dataset. Students must take at least 70 courses.
GPA1 – GPA8	0 – 4.00	Students' semester GPA from 1^{st} semester to 8^{th} semester
CGPA	0 – 4.00	Students' Cumulative GPA
Credit_total	0 – 158	Total Credits are taken by the student
Total_score	0 – 632	Total cumulative numeric score
Duration	1-10 (semester)	Current students' duration in the school

In this study, the dependent variables are served by a target feature, which is the on-time graduation feature. From Table 1, if the status of a student is graduate and the duration from Table 2 is equal to or less than 8 semesters, then it is on time. If the student's status is already graduated but the duration is more than 8 semesters, then that student is not on time for graduation. The possibility that there is a record of more than 8 semesters is because data collection was conducted from August to November 2023, which happened to be the 9th semester of the 2019 batch. Thus, if the status of students is still active, leave or drop, those are classified as not on time.

First Phase Process: Educational Data Mining

This research is structured around the CRISP-DM framework, a widely recognized methodology in data mining [23] that consists of six stages: Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment. The study integrates this framework with a horizontal sequence approach and adopts the Waterfall Model for software development, ensuring a systematic and sequential approach throughout the research process, as depicted in Figure 1.

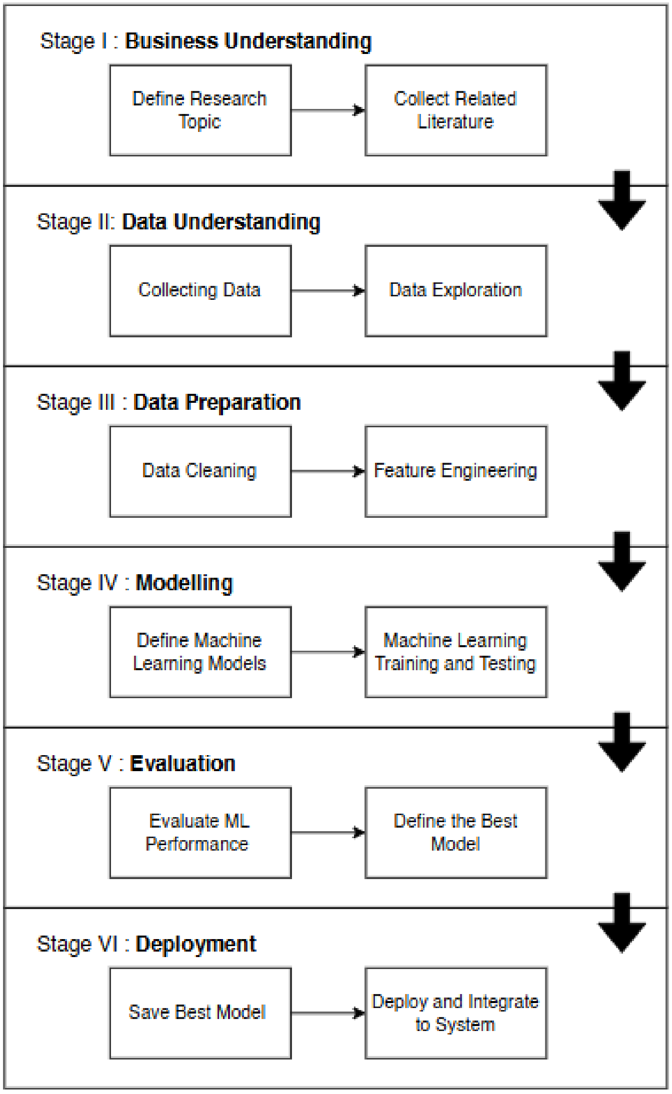

Figure 1. CRISP-DM Stages and Process

Stage I (June-July 2023) involved defining the research topic, reviewing relevant literature, and planning preliminary research activities. This stage focused on outlining the study's objectives and designing initial research schemes. Researchers anticipated and addressed potential challenges, such as bureaucratic delays in data collection and privacy concerns related to handling student demographic information. This preparation was crucial for ensuring a smooth transition to the subsequent stages.

Stage II (August-November 2023) centered on Data Understanding, which included the collection and exploration of data. Researchers faced several difficulties during this phase, including incomplete data records and bureaucratic hurdles within the academic system. Data collection required retrieving additional information from linked databases to fill gaps left by the primary academic system. The lack of adequate export functionalities in the academic system further complicated data retrieval, necessitating a combination of automation and manual efforts to compile a comprehensive dataset.

Stage III (December 2023-January 2024) focused on Data Preparation, a critical phase involving data cleaning and feature engineering. Researchers refined the dataset from an initial 539 records to 133 usable records. This process included matching records based on student identities and handling missing values. The dataset was also simplified through feature engineering, where raw data with 303 features was reduced to 51 features. This included demographic data, academic performance metrics, and courses that were categorized as described in Table 3, all of which were essential for building effective machine-learning models.

Table 3. Course Categorization

Course Category	Course Included
Mathematics	Logic, Math for Engineering, Physics, Math Discrete, Statistics, Linear Algebra, Algorithms Analysis, etc.
Programming	Algorithms and Programming, Programming 1, Programming 2, Software Engineering, Data Structure, etc.
Lab Programming	Programming 1 Laboratory, Database Laboratory, Artificial Intelligence Laboratory, Decision Support System Lab, etc.
Language	English, English for Engineering, Bahasa Indonesia
Electronical	Digital Engineering, IoT, Digital Processing, Electronics System Design, Microcontroller, etc.
Lab Electronical	Digital Engineering Laboratory, IoT Laboratory, Digital Processing Laboratory, Electronics Circuit Laboratory, etc.
Social_Science	Digital Transformation, Educational Psychology, Education Science, Entrepreneurship, Vocational Technology Education, etc.
Lab_Social_Science	Community Service, Teaching Practice, Internship
Science_Tech	Intro to IT, Computer Network, Computer and System Organization, Data Communication, Multimedia, etc.
Lab_Science_Tech	Computer Network Laboratory, Data Communication Laboratory, Multimedia Laboratory, etc.
Writing	Undergraduate Thesis, Research Methodology

Stage IV (February-March 2024) encompassed the Modeling phase, where several machine-learning algorithms were applied to the prepared dataset. Models such as Decision Tree, kNN, Logistic Regression, Random Forest, SVM, SGD, Naïve Bayes, Neural Network, and Gradient Boosting were developed and evaluated. Feature Importance analysis was conducted to identify which features had the most significant impact on predicting on-time graduation. This analysis aimed to optimize the efficiency and accuracy of the machine learning models.

Stage V (April 2024) involved Evaluation, where the performance of the developed models was rigorously assessed using standard metrics such as Accuracy, F1-score, and AUC. This stage was crucial for determining the most effective model based on its predictive performance. The evaluation process ensured that the selected model provided reliable and accurate predictions for on-time graduation.

Stage VI (April-May 2024) covered Deployment, which included developing a website-based system designed to provide data insights and predict on-time graduation. This system was built using the best-performing model identified in the Evaluation stage. The Waterfall Model was employed for the development process, ensuring a structured and sequential approach to system design and implementation. The deployment phase also involved user testing and feedback collection to refine the system and ensure it met the needs of educators and students.

Second Phase Process: System Development

The second phase of this research extends from Stage VI of the CRISP-DM framework through to the conclusion and writing of the study. This phase is centered on the development and deployment of a predictive analytics system using the best-performing model identified earlier in the research process. The second phase of the research process is described in **Error! Reference source not found.**.

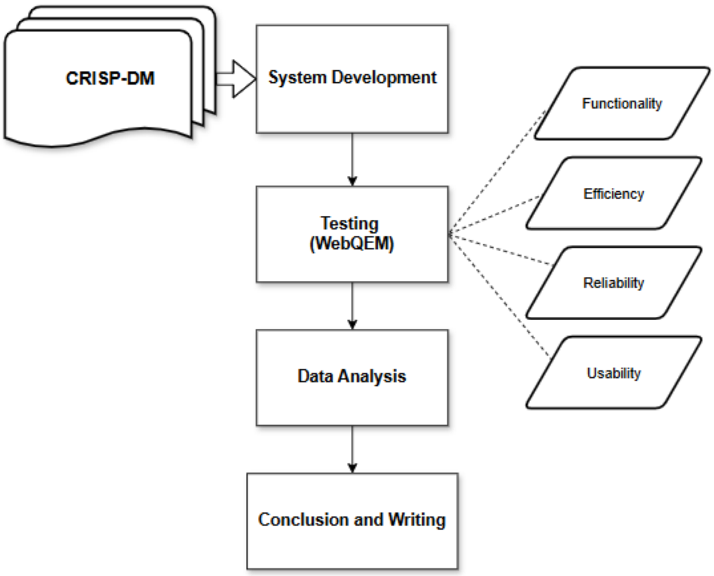

Figure 2. Second Phase of the Research Process

The System Development stage builds on the Deployment phase of CRISP-DM and employs the Waterfall Model for development. The focus is on creating a comprehensive web-based system that integrates features such as a Dashboard, Prediction tools, and a Data Explorer. This system aims to provide actionable insights and predictions based on the data.

In the Testing stage, the developed system undergoes rigorous testing according to the WebQEM criteria, which cover functionality, efficiency, reliability, and usability [24]. Functionality is tested through Pass-Fail assessments of system features [25]. Efficiency is evaluated using GTMetrix for web speed testing. Reliability is assessed through load testing with k6 to simulate stress conditions. Usability is examined via a 5-point Likert scale questionnaire based on Lund's USE questionnaire [26], involving feedback from educators and students who interact with the system.

The Data Analysis stage involves analyzing the collected dataset, evaluating machine learning model performance, reviewing software testing outcomes, and interpreting feedback from usability questionnaires. This analysis ensures a comprehensive understanding of the system's effectiveness and areas for improvement. Finally, the Conclusion and Writing concludes with the synthesis of findings and the preparation of a detailed thesis report, summarizing the study's results, insights, and implications.

RESULT AND DISCUSSION

Feature Importance

Feature importance is a crucial concept in machine learning and statistics, referring to the process of identifying the most influential variables in a dataset that contribute to the prediction of the target variable. By understanding which features hold the most significance, we can make informed decisions on data preprocessing, feature engineering, and model selection, ultimately leading to more accurate and efficient models. Feature importance is essential for enhancing model interpretability, reducing overfitting by eliminating redundant or irrelevant features, and improving computational efficiency.

Various techniques can be employed to assess feature importance, such as statistical tests, model-based approaches, and permutation methods, each offering unique insights into the data and model dynamics. In this case, we employed Feature Importance based on Logistic Regression and Random Forest model. The reason for conducting two features' importance is that we expected this process to be model-agnostic. The Logistic Regression model was chosen because it is widely used for binary classification problems, which suits our study case. Meanwhile, the Random Forest model was chosen because of its ability to capture complex, non-linear relationships between features and the target variable. Unlike linear models, Random Forest did not assume a linear relationship, making it suitable for a broader range of features in the case of our dataset.

Table 4. Feature Importance Score

Feature	***M***	***SD***
Gpa4	0.0695	0.0160
Cgpa	0.0203	0.0069
Extra_curr=yes	0.0169	0.0038
Programming	0.0164	0.0045
Sex=M	0.0113	0.0045
Toefl	0.0092	0.0011
Social_Science	0.0045	0.0004
F_Job=Employee	0.0040	0.0015
M_Job=Not Working	0.0040	0.0020
School_major=Science	0.0011	0.0008

This study investigates factors influencing on-time graduation. Based on the Feature Importance results that are described in Table 4, the findings indicate that the GPA in the 4th semester is a significant predictor of on-time graduation. We also conducted Pearson Correlation Analysis on these variables which were shown by the Feature Importance process. GPA in the 4th semester has a strong correlation (r = .243; **p = .005) and an average GPA of 3.70 among those who graduate on time. The Cumulative GPA (CGPA) emerges as a significant predictor, showing the highest correlation (r = .281; ***p = .001), with an average CGPA of 3.74 for on-time graduates.

Extracurricular activities, although not initially highlighted in the feature importance analysis, are significantly correlated with on-time graduation. Students involved in extracurriculars show a positive correlation (r = .292; ***p = .001), while those not involved exhibit a negative correlation (r = -.292; ***p = .001). Programming courses also have a positive correlation with on-time graduation (r = .257; **p = .003), although the data shows some variability, with certain high scorers still not graduating on time.

Gender is another influential factor, with female students positively correlated with on-time graduation (r = .211; *p = .015), whereas male students are negatively correlated (r = -.211; *p = .015). English proficiency, measured by TOEFL scores, shows an insignificant correlation (r = .041; p = .638), indicating minimal impact on graduation timing.

Social Science courses display a slightly stronger correlation with on-time graduation compared to Programming courses (r = .260; **p = .002), suggesting that performance in social sciences is also important. Parents' occupations, particularly the father's job as an employee, have a small but significant correlation with on-time graduation (r = .172; *p = .047), while the mother's occupation shows a low correlation, with the highest being for labour (r = .142; p = .104).

Lastly, the study examines the impact of high school majors on graduation timing. Both EEC and Science majors have significant frequencies compared to other majors, with EEC showing a positive correlation (r = .039; p = .353) and Science with a negative correlation (r = -.086; p = .323). This indicates that in the studied department, the students who majored in EEC in high school have a positive

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correlation towards on-time graduation. These results underscore the importance of academic performance, extracurricular engagement, and certain demographic factors in predicting on-time graduation, supported by detailed correlations and p-values.

Model Evaluation

In this study, various machine learning algorithms were employed to identify the best model for predicting on-time graduation, addressing the challenge of an imbalanced dataset using SMOTE (Synthetic Minority Oversampling Technique). SMOTE was used to generate synthetic samples for the minority class, which, as shown in Figure 3, improved model performance by mitigating bias and enhancing the accuracy of predictions [27]. The study evaluated models based on standard metrics like accuracy, F1-score, precision, recall, and AUC (Area Under the ROC Curve), with AUC chosen as the primary benchmark due to its effectiveness in ranking predictions [28], [29]. Table 5 shows all nine model evaluation scores based on AUC.

Table 5. Model Evaluation Score

Model	Accuracy	F1-Score	Precision	Recall	AUC
Random Forest	0.852	0.796	0.796	0.807	0.875
SGD	0.889	0.752	0.758	0.748	0.848
Gradient Boosting	0.778	0.762	0.761	0.763	0.837
SVM	0.889	0.635	0.607	0.715	0.836
Log Regression	0.852	0.729	0.724	0.748	0.815
Neural Network	0.815	0.744	0.739	0.759	0.815
kNN	0.593	0.665	0.654	0.715	0.772
Decision Tree	0.778	0.695	0.693	0.696	0.663
Naïve Bayes	0.407	0.794	0.854	0.781	0.630

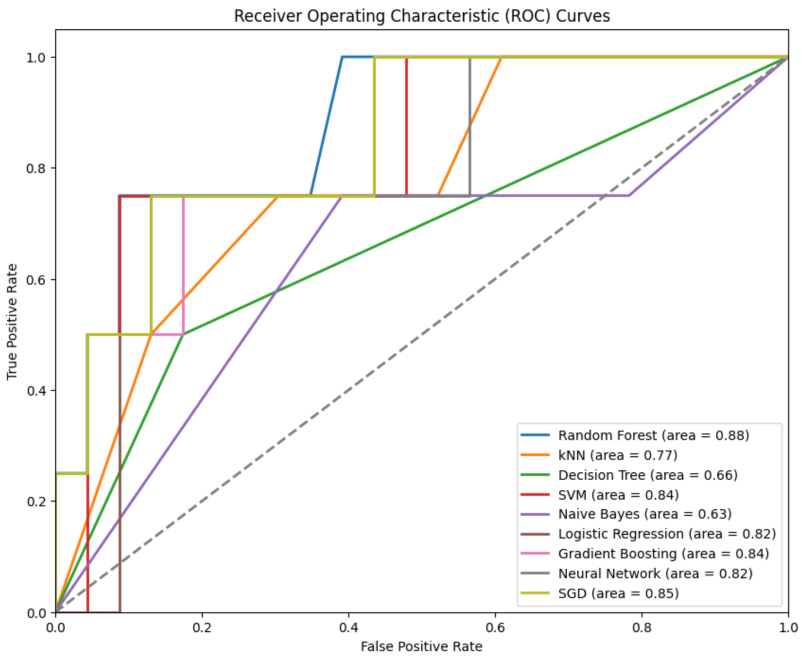

Figure 3. AUC (Area Under ROC Curve) Graph

The models compared include Random Forest, k-Nearest Neighbors (kNN), Decision Tree, Support Vector Machine (SVM), Naive Bayes, Logistic Regression, Gradient Boosting, Neural Network, and Stochastic Gradient Descent (SGD). Among these, the Random Forest model was selected as the best, with the highest AUC score of 0.875, indicating superior performance in distinguishing between students likely to graduate on time and those who are not. Other models, such as SVM, Gradient Boosting, and SGD, also performed well, with AUCs around 0.84, while Naive Bayes had the lowest AUC of 0.63. The study utilized ROC curves to represent each model's performance visually, confirming that ensemble methods like Random Forest are particularly effective in handling the prediction task when using SMOTE for dataset balancing. In contrast, Naive Bayes assumes feature independence, limiting its ability to account for the interactions between demographic and academic features, which are likely relevant for predicting graduation outcomes [30], [31]. Similarly, models like kNN and Decision Trees tend to be more sensitive to imbalanced data, even after applying SMOTE, potentially leading to less stable predictions and lower AUC scores.

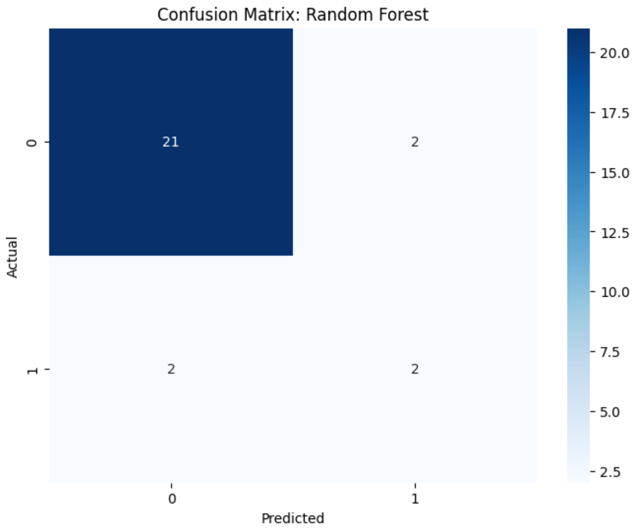

Figure 4. Confusion Matrix of Random Forest Model on Testing Data

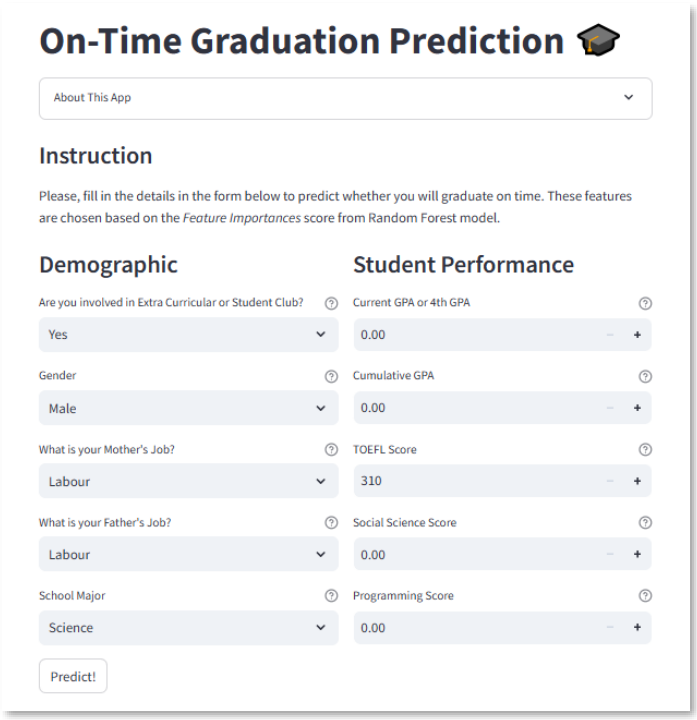

Figure 5. Prediction Feature Page

Correspondingly, we also conducted an evaluation using the Confusion Matrix of the best model, which can be seen in Figure 4. This Confusion Matrix used 20% (N=27) of the dataset set for the testing data, which has 21 accurate predictions of 0s (not-on-time graduation) and two accurate predictions of 1s (on-time graduation).

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System Performance

In this study, the WebQEM was utilized as the standard for evaluating web quality, specifically analyzing aspects of functionality, efficiency, and reliability to ensure robust system performance.

To assess functionality, BlackBox testing was conducted with a team of five software engineers, including three with over five years of experience. Participants from Taiwan and Indonesia used a Pass-Fail Decision checklist to evaluate the system. The results indicated a 99.4% pass rate, with all functions successfully passing in terms of completeness and appropriateness, except for one item in correctness. This outcome surpasses the General Availability (GA) criteria of 95% as recommended by Telcordia GR-282, confirming that the developed system meets the functionality standards [32].

Efficiency was evaluated through web speed testing using GTMetrix, a comprehensive tool for web performance analysis. The system's various pages were tested for metrics like Performance Score, Structure Score, and Largest Contentful Paint (LCP). GTMetrix testing from all pages in the web system resulted in 82.4% Performance score, 87.6% Structure score, 1.48s LCP, and Grade B of overall GTMetrix score. According to web performance standards, an LCP of under 2.5 seconds is generally considered acceptable, with 1.2-2.5 seconds seen as good performance and under 1.2 seconds as ideal [33], [34], [35]. Thus, the system’s LCP of 1.48s falls within the acceptable range, ensuring that users experience minimal delays. These results met the standard threshold for acceptable load times, adhering to the guidelines provided by Nielsen on user attention and response times [36].

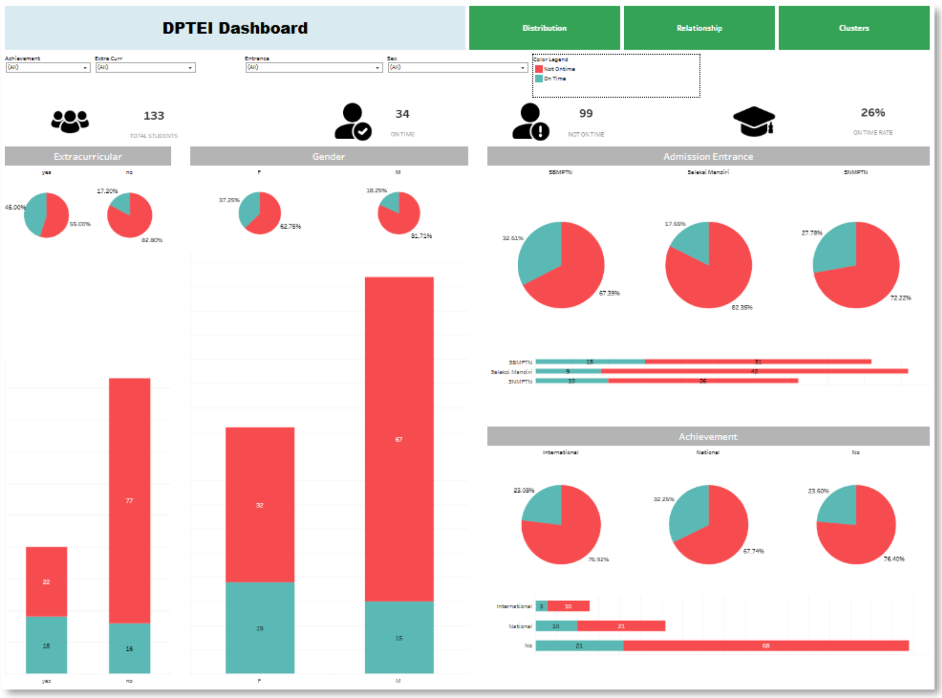

Figure 6. Dashboard Page

Reliability was assessed using stress testing via the k6.io tool to ensure the system's readiness for simultaneous access by multiple users. Two load testing scenarios were conducted, each lasting 10 minutes, with virtual users (VUs) ramping up from 10 to 50. The results demonstrated the system's capability to handle an average of 10 requests per second in the 20 VUs scenario and 28 requests per second in the 50 VUs scenario, with no HTTP request failures recorded. The average request duration was 388.79 milliseconds for 20 VUs and 159.08 milliseconds for 50 VUs, well within the acceptable range as defined by Google's standards for web response times [36].

These assessments collectively affirm that the developed system adheres to industry standards in terms of functionality, efficiency, and reliability, thus validating its readiness for deployment.

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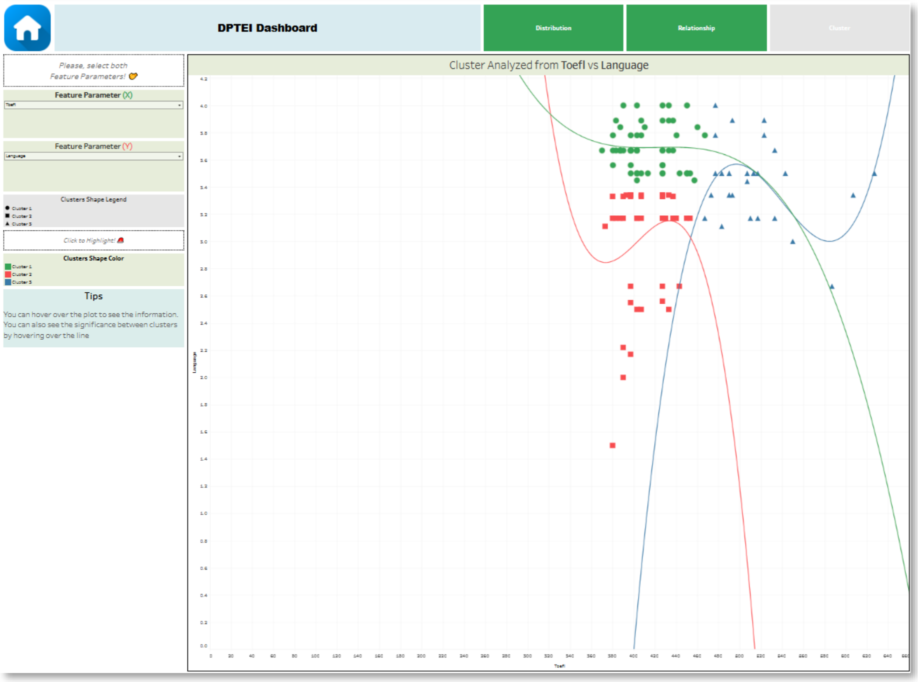

Figure 7. Cluster View on Dashboard Page

System Perception

In this study, system perception was analyzed through quantitative and qualitative data collected from educators and students, focusing on usability and expert opinions on functionality.

The analysis utilized Lund's USE Questionnaire, which has four dimensions: usefulness, ease of use, ease of learning, and satisfaction, and was administered to 36 participants (24 students and 12 educators) over a week in June 2024. The validity of the questionnaire was confirmed using Pearson's Product Moment, where all 30 items met the validity criteria (r count > r table, significance < 0.05). The reliability of the questionnaire was also confirmed, with an overall Cronbach's α of 0.973, indicating excellent internal consistency. Notably, neither party showed significant differences as the independent t-test was conducted. Hence, there is no need to separate the analysis of system perception.

Further analysis at the dimension level showed high reliability across all dimensions: usefulness ($\alpha = 0.896$), ease of use ($\alpha = 0.902$), ease of learning ($\alpha = 0.894$), and satisfaction ($\alpha = 0.955$). The mean scores and standard deviations for these dimensions indicated that user perception of the system was positive, with percentages ranging from 81.11% to 82.92%, as described in Table 6. Participants expressed high satisfaction with the system's intuitive interface and ease of navigation, while some suggested improvements in loading speeds for dashboard features. This feedback highlights areas of strength and opportunities for further refinement, ensuring the system meets user expectations.

Table 6. Questionnaire Dimension Results

Dimension	*M*	*SD*	Percentage
Usefulness	4.15	0.84	82.92%
Ease of Use	4.13	0.93	82.58%
Ease of Learning	4.10	0.97	82.08%
Satisfaction	4.06	0.91	81.11%

The qualitative analysis of feedback from educators and students regarding the developed system highlights both its strengths and areas for improvement. From the strength point of view, participants generally had a positive perception of the system. They appreciated its potential to enhance educational technology, streamline workflows, and support student success. Several users expressed hope that the system could be widely implemented, as it could benefit both the department and the university overall. The system was also recognized for its potential to motivate students by predicting their likelihood of graduating on time.

Despite the positive feedback, some users reported issues with system performance, such as lagging and slow server communication, particularly in the Dashboard's Relationship tab. There were also concerns about the initial user experience, with some participants finding the system confusing to use at first, especially in the Data Visualization Explorer. Suggestions for improvement included providing tutorials, optimizing loading speeds, and refining the UI/UX to accommodate users, such as senior lecturers, who expressed a need for a zoom feature in the dashboard to view better-detailed data and simpler navigation for accessing advanced filtering options.

CONCLUSION

The study developed a system aimed at helping educators and students improve graduation timeliness, which is crucial for enhancing workflow efficiency and contributing to better institutional reputation and accreditation. The system provides predictive analytics and insights to help students graduate on time, serving as a decision-support tool. Key findings include identifying significant factors like CGPA and extracurricular involvement, which positively influence on-time graduation. The Random Forest model was the most effective among nine predictive models, demonstrating high accuracy and reliability. The system passed the WebQEM standard, showing high functionality, efficiency, and reliability. Both students and educators expressed positive perceptions of the system, particularly in terms of usefulness, ease of learning, and overall satisfaction.

The study had limitations, including a small sample size of 133 student records and a focus on a single department, which may affect the generalizability of the findings. Future research could address these limitations by collecting a larger dataset across multiple departments to capture a broader range of student experiences and improve the robustness of the predictive models. Expanding data sources to include additional departments or institutions would allow for a more comprehensive analysis and enhance the model’s generalizability, enabling the system to be effectively adapted to a variety of academic contexts.

The system developed in this research is adaptable to other departments, indicating its versatility. The framework could be replicated in various academic units, enhancing graduation timeliness across different disciplines. The study also highlights the system's capability as an early warning mechanism, identifying at-risk students early in their academic journey, which allows for timely interventions by educators and administrators. This feature, while initially based on the GPA of the 4th semester, could be adjusted to earlier academic markers if proven effective.

The absence of such predictive systems in many Indonesian higher education institutions, particularly in the studied department, underscores the innovative and practical value of this research. The implementation of this system could revolutionize how institutions monitor and support student progress, leading to better educational outcomes. The study also opens up avenues for future research, particularly in exploring multiple linear regression models to provide detailed insights into factors affecting on-time graduation. Unlike the current approach, multiple linear regression could offer a numeric prediction of how close students are to meeting graduation timelines, providing a clearer, quantitative perspective on each predictor’s influence. This added precision would enable institutions to deliver more targeted interventions and personalized recommendations. These models could offer personalized recommendations, helping students achieve timely graduation by understanding the impact of various academic predictors.

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