



Student Dropout Risk Classification: A Comparison of Random Forest and Naïve Bayes Algorithms

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Abstract

Student dropout challenges higher education, while class imbalance can obscure models' ability to identify students at risk. This study compared Random Forest and Naïve Bayes using academic and nonacademic variables, emphasizing performance on the dropout class. Evaluation used 1,900 test records: 1,452 non-dropout and 448 dropout cases. Confusion matrices, classification metrics, a majority-class baseline, balanced accuracy, and Matthews correlation coefficient were examined. Naïve Bayes achieved 76.58% accuracy, exceeding Random Forest's 73.21% but barely surpassing the 76.42% baseline. For dropout detection, Random Forest achieved 0.20 recall and a 0.26 F1-score, compared with 0.05 and 0.09 for Naïve Bayes. Random Forest identified 91 dropout cases versus 22, with approximately 1.93 additional false alarms per additional case detected. Despite its relative advantage in detecting dropout, Random Forest missed 357 of 448 cases. Neither model is suitable as a primary early warning classifier without further improved handling of class imbalance and careful decision thresholds.

Keywords: Random Forest; Naïve Bayes; Study Hours; Stress Index; Family Income

Abstrak

Putus studi mahasiswa menjadi tantangan bagi perguruan tinggi, sedangkan ketidakseimbangan kelas dapat menyamarkan kemampuan model mengidentifikasi mahasiswa berisiko. Penelitian ini membandingkan Random Forest dan Naïve Bayes menggunakan variabel akademik serta nonakademik, terutama pada kinerja terhadap kelas putus studi. Evaluasi menggunakan 1.900 data uji, terdiri atas 1.452 mahasiswa tidak putus studi dan 448 mahasiswa putus studi. Matriks kebingungan, metrik klasifikasi, acuan kelas mayoritas, akurasi berimbang, dan koefisien korelasi Matthews dianalisis. Naïve Bayes mencapai akurasi 76,58%, melampaui Random Forest 73,21%, tetapi hampir sama dengan acuan kelas mayoritas 76,42%. Dalam mendeteksi putus studi, Random Forest memperoleh recall 0,20 dan F1-score 0,26, dibandingkan 0,05 dan 0,09 pada Naïve Bayes. Random Forest mendeteksi 91 kasus, sedangkan Naïve Bayes 22, dengan sekitar 1,93 alarm palsu tambahan untuk setiap kasus yang terdeteksi. Namun, Random Forest masih melewatkan 357 dari 448 kasus. Kedua model belum layak menjadi pengklasifikasi utama sistem peringatan dini tanpa penanganan ketidakseimbangan kelas dan penyesuaian ambang keputusan.

Kata-kata kunci: Random Forest; Naïve Bayes; Lama Belajar, Tingkat Stress, Pendapatan Keluarga



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1. Introduction

Universities have a strategic role in producing quality human resources [1] through the implementation of effective and sustainable education. However, one of the problems that higher education institutions still face is students who are unable to complete their studies or experience dropouts. The problem of dropouts not only has an impact on students, but can also affect graduation rates, the effectiveness of education delivery, student retention, reputation, and the management of institutional resources. Ramadhany and Wati's research shows that dropouts are a serious problem and early detection is needed so that universities can provide interventions, such as academic guidance, counseling, and financial assistance to at-risk students [2]. In line with this, Siagian et al.'s research emphasizes the importance of early identification of dropout risks so that academic actions can be provided more quickly and appropriately [1]. The phenomenon of student dropouts is a complex problem because it is influenced by various academic and non-academic factors. Academic factors can be in the form of achievements, attendance rates, late completion of assignments, and study progress, while non-academic factors can be related to economic conditions, demographic characteristics, psychological conditions, work, and the student environment [1] uses a combination of attributes such as gender, length of study, violations, GPA, absenteeism, parental income, leave and registration history, KIP status, and place of residence in identifying students who have the potential to dropout. International research also shows that non-academic characteristics have predictive value [3] found that age, program relevance, and number of working hours are some important indicators in predicting dropouts, while suggesting the integration of study-related information with socioeconomic and demographic indicators. The development of information technology and the digitalization of academic systems has caused universities to produce an increasing amount of student data. The data can be used not only as administrative documentation, but also as a source of knowledge to support decision-making. The data mining and machine learning approach allows students' historical data to be analyzed to find patterns related to study success and failure. Wijaya and Brotosaputro's study shows that algorithms such as Random Forest, Decision Tree, Support Vector Machine, Artificial Neural Network, and Graph Convolutional Networks have been widely used in predicting academic performance, with dataset quality, feature selection, and evaluation methods being factors that affect model performance [4]. Thus,

the machine learning approach has the potential to be used as part of an early warning system to detect at-risk students before dropout decisions actually occur. Various previous studies have applied machine learning algorithms to predict academic success and dropouts. Fansyuri and Yunita applied Naïve Bayes to academic and non-academic data of students. The model was evaluated using a confusion matrix, accuracy, precision, recall, and F1-score and produced an accuracy of 85%. The study shows that Naïve Bayes has the potential to be used as a basic model in supporting academic decision-making and the development of early warning systems [5]. The study also recommends further development through the addition of features, handling class imbalances, and comparisons with other algorithms. Meanwhile, decision tree-based algorithms also show potential in the classification of educational data. Tomori and Tomori compared C4.5, ID3, and CART using socioeconomic and demographic data and obtained an accuracy of 79.5%, 80%, and 78.5%, respectively [3]. The characteristics of the Decision Tree that generate the structure of the tree and the decision rules make it interesting in the context of education because the results of the classification can be traced through the attributes that shape the decision. The interpretability aspect becomes important when the predictive results are used by university managers as a basis for determining interventions on students.

Recent research also shows that algorithm performance can differ depending on the characteristics of the dataset and evaluation method. Comparing K-Nearest Neighbor, Naïve Bayes, and Random Forest with SMOTE on 4,424 student data. The results showed that Naïve Bayes was 65.99% accurate, while Random Forest obtained 76.72%, which shows that there is no one algorithm that universally provides the best performance for all data characteristics [6]. Ramadhany and Wati's research with Random Forest on 398 student data even obtained 97% accuracy, 98% accuracy, and 97% recall [2]. These differences in results indicate that the characteristics of attributes, class distribution, amount of data, and algorithms used need to be considered when building a dropout prediction model. In addition to classification performance, the interpretability aspect of the model is an issue that is getting more and more attention. A systematic study by Wijaya and Brotosaputro found that although the performance of various academic prediction algorithms continues to improve, the interpretability of results and generalization capabilities are still challenges [4]. The study of Bulut et al. also emphasizes the importance of explainability in the use of machine learning in educational environments because

model transparency can help stakeholders understand and validate the basis of a predictive decision [7]. This condition shows that the development of educational prediction models does not solely require high performance, but also needs to consider the model's ability to provide information that can be understood by decision-makers.

Although dropout prediction research has developed, there is still room for further study. First, previous research used a variety of algorithms, datasets, and attributes to produce different performances. Second, some studies focused on specific academic factors, while others used socioeconomic or demographic factors. The integration of academic and non-academic attributes in one evaluation framework can provide a more comprehensive representation of student conditions. Third, comparative research is needed to find out how algorithms with different characteristics work on the same dataset [8]. Decision Tree produces classification rules that are relatively easy to trace, while Naïve Bayes uses a probabilistic approach in determining the likelihood of membership in a class. Therefore, a comparison of the two on the same dataset and evaluation scheme can provide a more controlled picture of the performance characteristics of each model. This need is increasingly relevant because dropout data in practice can have an unbalanced distribution of classes. Rotifa et al.'s research states that the number of dropout students can be less than students who continue their studies, so the model has the potential to be biased towards the majority class [9]. The same research shows that the evaluation of dropout prediction models needs to consider several performance measures, such as accuracy, precision, recall, F1-score, and AUC, not just accuracy [9]. This is important because models with high overall accuracy may not necessarily have the same ability to detect students who are actually in dropout classes. Based on these gaps, this study compares Decision Tree and Naïve Bayes algorithms in predicting student dropouts using a combination of academic and non-academic data. The novelty of the study is directed at testing two classification approaches with different characteristics on the same dataset and testing scenarios, namely the decision rule-based approach through Decision Tree and the probabilistic approach through Naïve Bayes [10].

The evaluation was carried out using a confusion matrix, accuracy, precision, recall, and F1-score, paying special attention to the model's ability to recognize dropout classes. This approach is expected to not only provide information on classification performance, but also provide a more comprehensive basis for the development of a student early warning system.

Thus, this study aims to build and evaluate a student dropout prediction model using Decision Tree and Naïve Bayes algorithms based on a combination of academic and non-academic data and compare the performance of the two algorithms based on accuracy, precision, recall, and F1-score. The results of the study are expected to provide empirical information about the characteristics of the two models while supporting the development of an early warning system that can help universities identify students at risk of dropping out early.

2. Method

2.1 Research and Data Design

This study uses an experimental quantitative approach with supervised binary classification. Class 1 states students at risk of dropout (positive class) and class 0 states non-dropout students. Data are sourced from dataset sources, batch periods, and total amount of data. Academic variables include GPA, social studies, number of credits passed, and number of failed courses, while non-academic variables include scholarship status, parental occupation, age at the time of enrollment, and economic conditions.

2.2 Pre-processing and Testing Scheme

The pre-processing stage includes missing value handling, categorical variable encoding, and normalization when used. The data is divided into training data and test data with a division ratio scheme, e.g. 80:20, and random state/stratification settings, resulting in 1,900 test data. Both models are evaluated on the same test data for fair comparison. The model is not given a class balancing treatment (without oversampling or class weighting) in order to know the basic behavior of each algorithm against the imbalance of the confirmation data that no SMOTE/class weight is used.

2.3 Random Forest

Random Forest is an ensemble method that builds multiple decision trees from a bootstrap sample and selects a subset of random features at each split, then combines the entire tree's predictions through majority voting [11]. The separation criteria on trees measure the impurity of nodes, for example with Gini Impurity:

$$Gini(D) = 1 - \sum_{i=1}^m p_i^2 \quad (1)$$

where D is the dataset on the node, p_i the proportion of the sample class i , and m the number of classes. The final prediction for the feature vector x of the T tree is expressed as:

$$\hat{y} = \text{mode}\{h_1(x), h_2(x), \dots, h_T(x)\} \quad (2)$$

Configure the hyperparameters used: number of trees ($n_{\text{estimators}}$), maximum depth, and other parameters; or specify the library's built-in values.

Naïve Bayes is a probabilistic classifier based on Bayes' Theorem assuming that each attribute is conditionally independent of the class name the variant used, e.g. Gaussian Naïve Bayes [12] :

$$P(C|X) = \frac{P(X|C) \cdot P(C)}{P(X)} \quad (3)$$

If $X = (x_1, \dots, x_n)$ and assume attribute freedom, the posterior class is calculated as follows, and the class with the highest posterior is chosen as the prediction:

$$P(C|x_1, \dots, x_n) \propto P(C) \prod_{i=1}^n P(x_i|C) \quad (4)$$

2.4 Evaluation Metrics

The metric was calculated from the confusion matrix with TP (true detected dropout), TN (non-dropout detected true), FP (non-dropout predicted dropout, false alarm), and FN (missed dropout). Because the data is unbalanced, this study not only uses accuracy, but also precision, recall, F1-score, balanced accuracy, and MCC [13] :

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (5)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (6)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (7)$$

$$F1 - \text{Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (8)$$

$$\text{Balanced Accuracy} = \frac{\text{Recall} + \text{Spesifisitas}}{2}, \quad \text{Spesifisitas} = \frac{TN}{TN + FP} \quad (9)$$

$$MCC = \frac{TP \cdot TN - FP \cdot FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (10)$$

In addition, the model results are compared to the majority baseline, which is the accuracy of a naïve model that always predicts class 0. The performance of the dropout class (class 1) is the main focus because it is this class that is targeted by the early warning system.

3. Results and Discussion

Results and discussions can be made as a unit containing research findings and explanations

3.1 Present the results of the research

The test data consisted of 1,900 students. A total of 1,452 students (76.42%) were non-dropout and 448 students (23.58%) were dropout, resulting in a class imbalance ratio of 3.24 : 1 (Table 1). As a result, the model that always predicts non-dropouts will obtain an accuracy of 76.42% without detecting a single student at risk. This figure becomes the majority baseline in the next analysis.

Table 1. Class distribution on test data

Classes	Quantity (support)	Proportion (%)	Remarks
0 (non-dropout)	1.452	76,42	Mayoritas
1 (dropout)	448	23,58	Minoritas (target)
Total	1.900	100,00	Rasio 3,24 : 1

3.2 Result Classification Report

Table 2. Classification report Random Forest.

Kelas/Metrik	Precision	Recall	F1-Score
0	0.78	0.90	0.84
1	0.37	0.20	0.26
Accuracy	-	-	0.73
Macro Avg	0.58	0.55	0.55
Weighted Avg	0.69	0.73	0.70

Table 3. Classification report Naïve Bayes.

Kelas/Metrik	Precision	Recall	F1-Score
0	0.77	0.99	0.87
1	0.54	0.05	0.09
Accuracy	-	-	0.77
Macro Avg	0.65	0.52	0.48
Weighted Avg	0.72	0.77	0.68

Overall, Naïve Bayes looked better with an accuracy of 0.77 compared to 0.73 in Random Forest. However, the picture was reversed in the dropout class. Random Forest obtained a recall of 0.20 and an F1 score of 0.26, while Naïve Bayes had only 0.05 and 0.09. In contrast, Naïve Bayes had a higher accuracy of the dropout class (0.54 compared to 0.37), but the value resulted from a very small number of positive predictions. The macro average F1-score, which treats both classes equally, was also higher in Random Forest (0.55 versus 0.48).

3.3 Result Confusion Matrix

Figure 2 shows the confusion matrix of the two models. Out of 448 dropout students, Random Forest detected 91 students (TP) and missed 357 students (FN). Naïve Bayes only detected 22 students (TP) and missed 426 students (FN). On the other hand, Random Forest generated 152 false alarms (FP), while Naïve Bayes only 19.

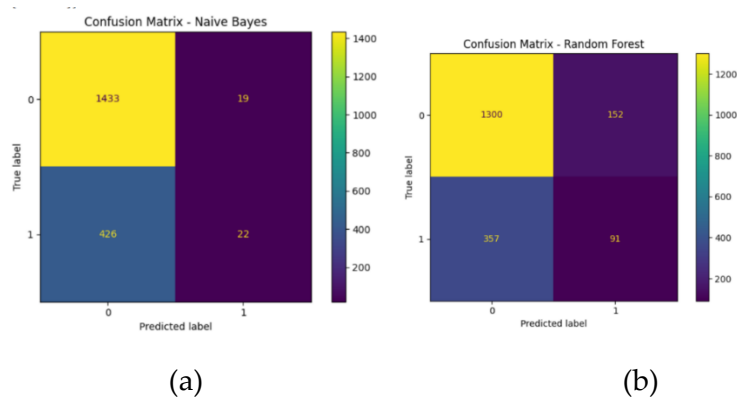


Figure 2. Confusion matrix (a) Random Forest and (b) Naïve Bayes on test data (program output). The values in the confusion matrix are used to lower additional metrics that are not displayed in the classification report, namely false negative rate, false positive rate, balanced accuracy, MCC, and lift to the basic proportion of the dropout class.

Table 4. Components of confusion matrix and derived metrics

Components / matrix	Random Forest	Naïve Bayes
TP (dropout detected)	91	22
FN (Late dropout)	357	426
FP (False alarms)	152	19
TN (non-dropout true)	1.300	1.433

3.4 Discussion

3.4.1 The Paradox of Accuracy

The Naïve Bayes accuracy (76.58%) was only 0.16 percentage points above the majority baseline (76.42%), and the accuracy of Random Forest (73.21%) was below that baseline. This means that, in pure accuracy, there is no better model than the simple strategy of predicting all students as non-dropouts. The Naïve Bayes accuracy that appears to be superior mainly comes from the 0th grade recall that reaches 0.99, i.e. almost all non-dropout students are predicted correct because the model rarely labels dropouts (only 41 out of 1,900 students, or 2.16%). These findings confirm that accuracy is not a viable metric for choosing an early warning model on unbalanced data.

3.4.2 Ability to Detect Dropout Students

In the targeted classes, Random Forest was consistently better: recall 20.31% to 4.91%, F1 score 0.26 to 0.09, balanced accuracy 54.92% to 51.80%, and MCC 0.125 to 0.105. Naïve Bayes' balanced accuracy of only 1.80 points above 50% shows its ability to distinguish the two classes almost equal to random guessing. However, Random Forest's advantage is relative: 357 out of 448 dropout students (79.69%) still missed. The MCC value of around 0.1 indicates that the correlation between the prediction and the actual condition of the two models is still weak.

3.4.3 The Trade-off Between False Detection and Alarm

Compared to Naïve Bayes, Random Forest detected 69 additional dropout students (91 versus 22), but with 133 additional false alarms (152 versus 19). In other words, every single additional student at risk detected required the handling of approximately 1.93 mislabeled non-dropout students. For academic units, this is a policy choice: when the initial intervention is low-cost (e.g. counselling or reminder messages), additional false alarms are relatively acceptable to reach more at-risk students; when interventions are expensive, precision is more important. Both models also have lifts above 1 (1.59× for Random Forest and 2.28× for Naïve Bayes), which indicates that academic and nonacademic variables contain predictive signals, but they have not been optimally utilized at the standard decision threshold.

3.4.4 Interpretation of Model Behavior Differences

The behavior of the two models can be explained conceptually, although the study did not test the cause experimentally. In Naïve Bayes, the large probability of class 0 prior (about 0.76) is

multiplied by the likelihood calculated under the assumption of attribute freedom. When academic and nonacademic attributes are correlated with each other, the likelihood tends to be overcalculated, and posterior dropout classes rarely exceed the 0.5 threshold, so few students are labeled dropout, and those labeled are generally at extreme conditions (explaining high precision with very low recall). Random Forest can capture non-linear relationships and inter-feature interactions so that more dropout cases are detected, but without class weighting or data balancing, the trees remain skewed toward the majority class. This conjecture is consistent with the literature emphasizing the need for class balancing on dropout predictions [14], and needs to be further tested through controlled experiments.

3.4.5 Implications for Early Warning Systems

Based on the above results, two practical implications can be formulated. First, the selection of models for early warning systems should be based on recall, F1-score, or balanced accuracy of dropout classes, rather than accuracy. Second, both models in their current configurations are not yet feasible to be used as the main engine of early warning systems. Before implementation, it is necessary to address class imbalances (e.g., class weighting, SMOTE, or other oversampling [15] adjustment of decision thresholds based on intervention costs, as well as stronger evaluation with cross-validation and precision-recall curves.

3.4.6 Limitations of the Study

This study has several limitations. First, the evaluation was carried out on one test data so that there was no estimate of performance variation or significance test between models. Second, no class imbalance was handled, hyperparameter adjustment, or decision threshold adjustment. Third, the analysis of the importance of features has not been carried out so that the dominant factor causing dropout cannot be concluded. Fourth, the explanation of the differences in model behavior is interpretive and has not been tested through ablation experiments.

4. Conclusion

Based on the results of the research, it can be concluded as follows:

- a. Naïve Bayes produced higher accuracy (76.58%) than Random Forest (73.21%), but this accuracy was almost the same as the majority baseline (76.42%) so it did not reflect the ability to detect dropout students.

- b. In the dropout class, Random Forest was superior with a recall of 0.20, F1-score of 0.26, balanced accuracy of 54.92%, and MCC of 0.125, compared to Naïve Bayes with a recall of 0.05, F1-score of 0.09, balanced accuracy of 51.80%, and MCC of 0.105. Random Forest detected 91 students at risk, while Naïve Bayes was only 22.
- c. Random Forest's detection advantage is gained by 133 additional false alarms, or about 1.93 false alarms for each additional dropout case detected. 4. Both models are not yet worthy of being the main engine of the early warning system in the current configuration because about 80% (Random Forest) to 95% (Naïve Bayes) of dropout students are still missed.v5.

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References

- [1] R. Forest *et al.*, "Klasifikasi Risiko Dropout Mahasiswa Menggunakan Algoritma Random Forest pada Dataset Predict Students ' Dropout and Academic Success Novita Sari Siagian¹, Monica Sari Batubara², Leony Sinaga³ ¹Program Studi Ilmu Komputer, Fakultas Matematika dan Ilmu," vol. 10, no. 2, pp. 629–640, 2026.
- [2] M. Zalina Ramadhany and L. Wati, "Klasifikasi Mahasiswa Berpotensi Drop Out (Do) Menggunakan Algoritma Random Forest," *JATI (Jurnal Mahasiswa Teknik Informatika)*, vol. 10, no. 2, pp. 3543–3548, 2026, doi: 10.36040/jati.v10i2.17666.
- [3] R. Adekola, T. Abdulfatai, and A. Tomori, "Predicting and Analysing Adult Learners Dropout Indicators From Literacy Programmes Using Data Mining Approaches," *Res. Sq.*, pp. 1–14, 2023, [Online]. Available: <https://doi.org/10.21203/rs.3.rs-3221091/v1>
- [4] V. Y. D. Wijaya and G. Brotosaputro, "Penerapan Data Mining Dalam Prediksi Kinerja Akademik Mahasiswa Menggunakan Algoritma Machine Learning," *Jurnal Infomedia: Teknik Informatika, Multimedia, dan Jaringan*, vol. 10, no. 2, pp. 134–142, 2025.
- [5] M. Fansyuri and D. Yunita, "Analisis Kinerja Algoritma Naive Bayes dalam Memprediksi Kelulusan Mahasiswa Menggunakan Python," *Jurnal Pustaka AI (Pusat Akses Kajian Teknologi Artificial Intelligence)*, vol. 5, no. 3, pp. 716–723, 2025, doi: 10.55382/jurnalpustakaai.v5i3.1491.
- [6] R. Sumitro and J. Ismail, "JUTEK – JURNAL TEKNOLOGI Komparasi Algoritma K-Nearest Neighbor, Naïve Bayes, dan Random Forest dengan SMOTE untuk Prediksi Dropout Mahasiswa," vol. 3, no. 1, pp. 18–25, 2026.

- [7] O. Bulut, T. Wongvorachan, S. He, and S. Lee, "Enhancing high-school dropout identification: a collaborative approach integrating human and machine insights," *Discover Education*, vol. 3, no. 1, 2024, doi: 10.1007/s44217-024-00209-4.
- [8] J. Niyogisubizo, L. Liao, E. Nziyumva, E. Murwanashyaka, and P. C. Nshimyumukiza, "Predicting student's dropout in university classes using two-layer ensemble machine learning approach: A novel stacked generalization," *Computers and Education: Artificial Intelligence*, vol. 3, p. 100066, 2022.
- [9] A. N. Rotifa, F. T. Alfini, P. C. Wardhana, and A. S. A. Putri, "PERBANDINGAN MODEL MACHINE LEARNING UNTUK PREDIKSI DROP-OUT MAHASISWA DENGAN ANALISIS FEATURE IMPORTANCE BERBASIS STUDI LITERATUR," vol. 10, no. 4, pp. 5595–5605, 2026.
- [10] R. Zulkifli *et al.*, "PENERAPAN ALGORITMA NAIVE BAYES DALAM MEMPREDIKSI MINAT MAHASISWA BARU Informatika Universitas Siliwangi Abstraksi Keywords : Pendahuluan Tinjauan Pustaka Data mining adalah proses penemuan pola dan," *Journal of Information System Management (JOISM)*, vol. 7, no. 2, pp. 252–259, 2026.
- [11] A. R. Dikananda, I. Ali, Fathurrohman, R. Ade Rinaldi, and Iin, "Genre e-sport gaming tournament classification using machine learning technique based on decision tree, Naïve Bayes, and random forest algorithm," *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 1088, no. 1, p. 012037, Feb. 2021, doi: 10.1088/1757-899x/1088/1/012037.
- [12] A. Meiriza, E. Lestari, P. Putra, A. Monaputri, and D. A. Lestari, "Prediction graduate student use naive bayes classifier," in *Sriwijaya International Conference on Information Technology and Its Applications (SICONIAN 2019)*, Atlantis Press, 2020, pp. 370–375.
- [13] R. Prasetya and A. Ridwan, "Data Mining Application on Weather Prediction Using Classification Tree, Naïve Bayes and K-Nearest Neighbor Algorithm With Model Testing of Supervised Learning Probabilistic Brier Score, Confusion Matrix and ROC," 2019.
- [14] J. Yuan, X. Qiu, J. Wu, J. Guo, W. Li, and Y.-G. Wang, "Integrating behavior analysis with machine learning to predict online learning performance: A scientometric review and empirical study," 2024, [Online]. Available: <http://arxiv.org/abs/2406.11847>
- [15] R. Stinebrickner and T. Stinebrickner, "Academic performance and college dropout," *J. Labor Econ.*, vol. 32, no. 3, pp. 601–644, 2014.