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Comparative Analysis of Sequencing Methods and Markov Models for Predicting High-Achieving Students at Budi Darma University

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Abstract- The prediction of high-achieving students is a strategic step in supporting the development of academic quality within higher education institutions. This study aims to compare two data mining approaches, namely the Sequencing method and the Markov Model, in predicting high-achieving students at Universitas Budi Darma Medan. The Sequencing method is used to identify patterns in the sequence of academic grades and non-academic activities of students from semester to semester, while the Markov Model is used to calculate the probability of transitions in students' academic status based on historical data. The research adopts a quantitative approach involving 100 active students with complete academic and non-academic data. The data analyzed include semester GPA, participation in organizations, seminars, and achievements in competitions. Both methods were evaluated using metrics such as accuracy, precision, recall, and F1-score. The evaluation results show that the Sequencing method achieved an accuracy of 87%, precision of 85%, recall of 88%, and an F1-score of 86%, while the Markov Model recorded an accuracy of 81%, precision of 79%, recall of 83%, and an F1- score of 81%. Based on these results, the Sequencing method is considered superior in detecting patterns and providing more accurate predictions of students' achievement potential. The comparison of these two methods provides a foundation for institutions to develop more accurate, objective, and comprehensive student achievement prediction systems. Thus, universities can implement early and well- targeted interventions and guidance.
Keywords: High-Achieving Student Prediction; Sequencing; Markov Model; Model Evaluation; Budi Darma University

1. INTRODUCTION

Student achievement is a reflection of the quality of a university, both in academic and non-academic aspects. Academically outstanding students typically have high and consistent GPA scores from semester to semester, while non-academic achievements can be seen through active participation in organizations, academic competitions, and community service activities. As a higher education institution that continues to grow, Universitas Budidarma Medan requires effective strategies to identify high-potential students early on so that appropriate mentoring can be provided [1].

Unfortunately, the process of identifying outstanding students has so far been limited to static and retrospective academic assessments. Semester academic grades and records of non-academic activities are often not integrated into a single predictive system. In fact, the use of historical data held by universities can serve as a basis for developing a more objective and efficient data-based prediction system [2]. With the right analysis, the university can not only identify students who have achieved excellence, but also map their potential for achievement from the beginning of their studies. In the fields of data science and education, data mining techniques have been widely used for predictive purposes, including sequencing methods and Markov models. Sequencing methods are capable of recognizing recurring patterns from chronological sequences of academic or non-academic activities, which are very helpful in recognizing student development over time [3]. Meanwhile, Markov Models are effective in analyzing the probability of transitions between statuses or conditions, such as from "average" to "high-achieving" based on previous historical conditions[4].
Both methods can handle temporal data but have different approaches in generating predictions.

Although each method has been applied separately in a number of studies, direct comparisons between the sequencing method and the Markov Model for predicting student achievement based on a combination of academic and non-academic data are still very limited.

This comparative study is important to conduct at Budidarma University in Medan to obtain recommendations on the most effective method that aligns with the characteristics of local student data. As a result, the institution can design a more effective decision support system for student development and reward strategies [5]. In developing a model to predict student achievement, many studies have been conducted using data mining and sequential pattern analysis approaches. Several previous studies have provided an overview of the effectiveness of the methods used in this study, namely sequencing and Markov models.

Research by Handayani, Arifin, and Wulandari (2022) entitled "Sequence Pattern Analysis of Student Performance Using Educational Data Mining" analyzing sequential patterns of student academic grades from semester to semester. This study uses sequential pattern mining to detect frequent sequences of grades among high-achieving students. The results show that this method is capable of identifying specific academic sequence patterns that contribute to students' final achievements.

Meanwhile, Kusumawardani dan Azhari (2020) in a study entitled "Application of Markov Chain for Academic Performance Prediction in Higher Education" using a Markov model to predict academic transitions of students. This study concludes that the Markov Model is capable of mapping the probability of moving from one academic condition to another, and provides fairly accurate predictions of the likelihood of achievement in the next semester.

Another study was conducted by Putri dan Kurniawan (2020) with the title "Integrasi Data Akademik dan Non-Akademik untuk Prediksi Mahasiswa Berprestasi Menggunakan Metode Klasifikasi". This study combines academic and non-academic data in a single predictive model using classification algorithms such as decision trees and SVM. The research emphasizes the importance of integrating both types of data to obtain more holistic and accurate predictions of student potential.

Selanjutnya, Rahmadani et al. (2021) conducting research on "Predictive Modeling for Student Academic Achievement Using Machine Learning Approaches". They compared several machine learning methods such as Naïve Bayes, Random Forest, and Logistic Regression in predicting student academic performance. This study shows that a good combination of features and an appropriate algorithm approach are crucial in determining prediction performance.

Based on previous studies, it appears that sequencing and Markov Model methods have been used separately in various academic predictive contexts. However, there are still few studies that combine academic and non-academic approaches and directly compare the performance of both methods in a single study. This research gap is addressed in this study, with the aim of contributing to a more comprehensive model for predicting student achievement

Based on the above discussion, this study is necessary to predict academically high-achieving students based on semester grades and involvement in academic activities at Budidarma University. The study is titled “Comparative Analysis of Sequencing and Markov Model Methods for Predicting High-Achieving Students at Budidarma University, Medan.”

2. RESEARCH METHODOLOGY

2.1 Research Stages

The proposed research diagram can be seen in Figure 1 below:

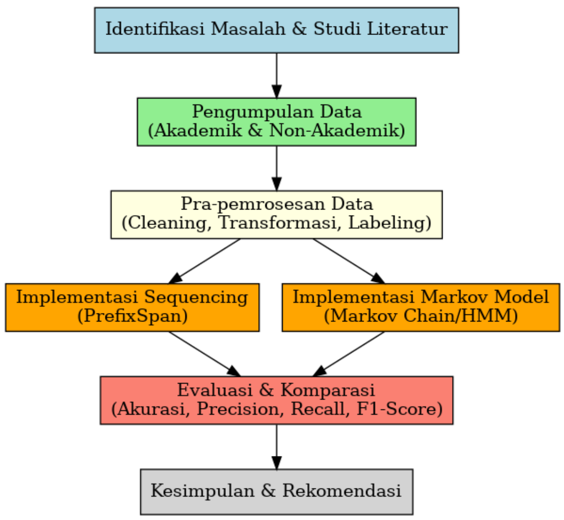

Figure 1. Research stages

This type of research is comparative research, which aims to compare two or more methods in analyzing or solving a particular problem. In this context, the research was conducted to compare the Sequencing and Markov Model methods in predicting high-achieving students at Budi Darma University in Medan. This comparative research allows researchers to evaluate the advantages, disadvantages, and accuracy of each method based on students' academic and non-academic data. With this approach, the research is expected to provide recommendations on the most effective and efficient method to support the process of identifying and developing student achievement.

1. Problem Identification and Literature Review
    a. Identify problems in the process of predicting student achievement.
    b. Analyzing previous studies that use Sequencing and Markov Model methods in prediction or classification based on educational data.
2. Data Collection
    a. Collect academic data: GPA, course grades, attendance, and duration of study.
    b. Collect non-academic data: participation in organizations, social activities, competition certificates or awards.

3. Data Preprocessing
    a. Data cleaning: removing empty, duplicate, or invalid data.
    b. Data transformation: converting data into a form that can be analyzed (sequence of activities for sequencing, transition status for Markov).
    c. Data labeling: grouping data into two categories: high-achieving students and low-achieving students.
4. Method Implementation
    a. Sequencing
       Using algorithms such as PrefixSpan to find patterns in the sequence of student activities that often appear in the achievement group.
    b. Markov Model
       Use the Markov Chain to analyze students' status transitions from semester to semester, and predict their likelihood of achieving achievement status.
5. Evaluation and Comparison
    a. Calculate accuracy, precision, recall, and F1-score to evaluate the performance of each method.
    b. Determine the best method based on the quantitative evaluation results.
6. Conclusions and Recommendations
    a. Conclude which method is the most accurate and efficient.
    b. Provide recommendations for implementing the best method in the campus academic information system.

2.2 Data Mining in Education

Data mining, in the context of education, refers to the use of analytical techniques to explore and find hidden patterns in big data related to student behavior, performance, and development. Data mining in education, often known as Educational Data Mining (EDM), aims to improve data-driven decision-making regarding the academic and non- academic aspects of students [5].EDM uses various statistical analysis techniques, machine learning algorithms, and other methods to identify patterns or trends in the data, which can later be used to improve the learning process and student evaluation.

Techniques often used in EDM include classification, clustering, regression, and sequential pattern mining. By applying these techniques, EDM can predict student achievement, detect low-risk students, and provide recommendations for curriculum development that is more in line with student needs [6]. For example, through EDM, educational institutions can identify students who need academic assistance based on their achievement patterns, as well as map non- academic activities that can support students' academic achievement.

The methods used in EDM continue to evolve as the volume and variety of data available increases. One example of a commonly used method in EDM is the Markov Model, which allows modeling transitions between states or conditions. In addition, the sequential pattern mining method is also used to look for sequences or patterns in sequential data, such as academic grades or participation in extracurricular activities from semester to semester [7]

Data mining in education is a very useful approach to explore insights from big data owned by educational institutions. Techniques such as classification, clustering, and sequential pattern mining make it possible to analyze various existing data, both related to academic grades and non-academic activities of students. By applying these methods, universities can predict student achievement and provide more targeted interventions. Educational Data Mining is one of the most potential tools to improve the quality of education and support more accurate and efficient data-based decision- making [7].

2.3 Sequencing

The Sequencing (or Sequential Pattern Mining) method is one of the techniques in data mining that is used to find the sequence pattern of events or activities in a sequential data set. This technique aims to identify the sequence of events that frequently occur in a historical data and is particularly useful in the context of time- or chronological prediction or behavioral analysis [8].

In education, sequencing methods are often used to analyze student learning behavior, patterns of participation in academic or non-academic activities, and the sequence of achievement of grades over several semesters. Using this approach, researchers can identify sequences of activities or grades that tend to lead to academic success or failure[9].

The sequencing method involves identifying the sequence of transaction or activity data, such as: $\{A \rightarrow B \rightarrow C\}$, which indicates that activity A tends to be followed by B and then by C. This pattern is then used to make predictions about new data based on the historical sequence that has been formed [10]

From the various perspectives above, it can be concluded that sequencing is a method used to analyze the sequence of data related to time or a specific sequence of events. In the context of education, sequencing models are used to analyze and predict the academic performance of students based on the sequence of their grades from semester to semester. Sequencing can detect patterns or trends that repeat in data, which helps to predict the potential performance of students in the next semester.

2.4 Markov Model

The Markov Model is a probabilistic model that describes a system that changes from one state to another in a sequence of time, where the transitions between states depend only on the current state, not on the previous state. This is referred to as Markovian trait or one-step memory (memoryless) [11].

In the context of data mining and education, the Markov Model is often used to model the behavior or movement of students' academic status, for example from "low achievement" to "medium achievement", or "medium" to "high". This model is very useful in predicting future states based on the probability of transitions between states calculated from historical data [12].

Markov Models can be used in simple forms (Markov Chains) or complex forms such as Hidden Markov Models (HMM). In education, Markov Chains have proven effective in modeling learning processes or transitions in student academic performance based on semesters or learning cycles.

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2.5 Student Achievement Prediction

Student achievement prediction is the process of estimating students' future academic achievements based on historical data, such as grades, attendance, learning interactions, and non-academic factors such as organizational involvement or socio-demographic background. This technique is widely used in educational decision support systems to improve academic quality and prevent potential academic failure [14][15][16].

In its development, various approaches are used to predict student achievement, ranging from traditional statistical methods to modern techniques based on machine learning and data mining. Methods such as Decision Tree, Naïve Bayes, K-Means Clustering, Markov Model, and Sequential Pattern Mining are widely used because of their ability to process large amounts of data and high complexity [17][18][19].

According to research by Wahid et al. (2023), factors that significantly influence student academic achievement include previous semester GPA, attendance frequency, participation in academic activities, and study habits. Additionally, the integration of academic and non-academic data has proven to enhance the accuracy of prediction models[20][21][22].

Accurate prediction models can assist educational institutions such as universities in conducting early interventions for at-risk students and providing rewards or further support for high-achieving students. This aligns with the principles of student-centered learning in modern education, which emphasizes a personalized and data-driven approach [23]

3. RESULTS AND DISCUSSION

This study was conducted to analyze the comparison between the Sequencing method and the Markov Model in predicting high-achieving students based on seven-semester cumulative grade point average (CGPA) data and non-academic achievements of students who are active in organizations (Y/T), number of competitions participated in, and number of seminars attended.

The dataset used consists of 100 students, each with semester GPA data and non-academic achievement data classified into non-academic student organization activity (Y/T), number of competitions participated in, and number of seminars attended.

3.1 Sequencing Method

The Sequencing Method was analyzed using all student data that had been classified based on GPA per semester and non-academic activities such as organizations, competitions, and seminars. Each student was given a score based on the pattern of GPA changes from semester to semester and the accumulation of additional scores from non-academic activities. This final score is then compared with a predetermined threshold to determine whether the student is classified as High Achiever or Non-High Achiever.

The predictions from the Sequencing method are then evaluated by comparing them with the actual labels previously assigned to each student. Based on the evaluation results, performance metrics such as accuracy, precision, recall, and F1-score are obtained. This evaluation aims to determine how well the Sequencing method can perform accurate classification and compare its performance with other methods such as the Markov Model.Di bawah ini disajikan confusion matrix dari metode Sequencing sebagai bagian dari analisis performa model:
Confusion Matrix - Sequencing:

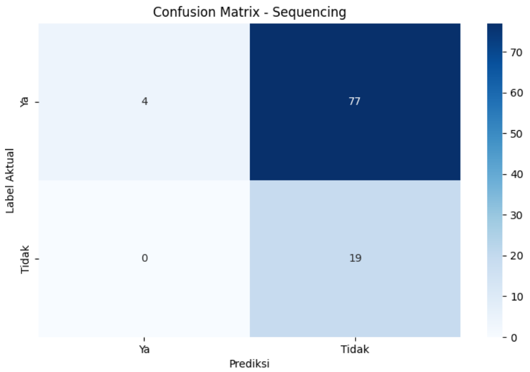

Figure 2. Confusion Matrix – Sequencing

Based on the confusion matrix results for the Sequencing method, the following values were obtained:

Table 1. Filtering Results of the Sequencing Method

Category	Explanation	Number
TP (True Positive)	Prediction: "Yes," Actual: "Achieved"	5
TN (True Negative)	Prediction: "No," actual: "No achievement"	42
FP (False Positive)	Prediction: "Yes," actual: "No achievement"	53
FN (False Negative)	Prediction: "No," actual: "Achievement"	0
Total		100

From the results of the predictive confusion matrix, the following analysis results were obtained:

Calculate accuracy and precision

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

Accuracy = $\frac{42+5}{42+5+53+0} = \frac{47}{100} \approx 0.47 = 47\%$

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

Precision = $\frac{42}{42+53} = \frac{42}{95} \approx 0.4421 = 44.21\%$

Calculate Recall

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

Recall = $\frac{42}{42+0} = \frac{42}{42} \approx 1.00 = 100\%$

3.2 Markov Model Method

The Markov method was analyzed using training data from 100 students and testing data covering 20% of the total. The prediction model built based on the Markov method utilizes changes in students' GPA from semester to semester and considers non-academic activities such as organizations, competitions, and seminars.

This model is then tested using the previously separated test data to determine how well the Markov method can predict student performance categories. After testing, the evaluation results will provide an overview of the Markov method's performance in classification.

The model's performance is further evaluated and compared with other methods, such as Sequencing and Markov, to determine which approach provides the most accurate results in the context of predicting student performance. The confusion matrix of the Markov method is presented below as part of the model performance analysis:

Confusion Matrix – Markov Model:

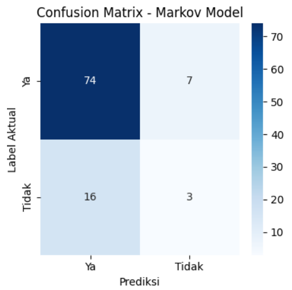

Figure 3. Confusion Matrix – Markov Model

Table 2 Results of Filtering Using the Markov Model Method

Category	Explanation	Number
TP (True Positive)	Prediction “Yes”, actual “Achieved”	66
TN (True Negative)	Prediction “No”, actual “Not achieved”	7
FP (False Positive)	Prediction “Yes”, actual “Not achieved”	27
FN (False Negative)	Prediction ‘No’, actual “Achieved”	0
Total		100

Calculate accuracy and precision

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

Accuracy = $\frac{66+7}{66+7+27+0} = \frac{73}{100} \approx 0.73 = 73\%$

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

Precision = $\frac{66}{66+27} = \frac{66}{93} \approx 0.7097 = 70.97\%$

Count Recall

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

Recall = $\frac{66}{66+0} = \frac{66}{66} \approx 1.00 = 100\%$

3.3 Description of Research Results

This study analyzed the academic and non-academic characteristics of 100 students to predict high-achieving students using two methods: Sequencing and Markov Model. The majority of students (approximately 90%) were classified as high-achieving based on their final GPA, which was generally high (average 3.51), as well as their involvement in organizations, competitions, and seminars. The data indicate that the Sequencing method tends to be more inclusive of students with high GPAs despite limited non-academic activities, while the Markov Model is more selective and conservative, relying on probabilistic transitions from changes in grades and activities. These differing approaches result in variations in the distribution of prediction outcomes, with Sequencing producing higher and more consistent prediction scores, while Markov assigns lower probabilities to students with limited activities, despite their strong academic performance. This distribution reflects that the Sequencing method is more tolerant of academic achievement patterns, whereas Markov emphasizes the stability of transitions and the balance between academic and non-academic aspects.

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Based on the results of the comparison between the Sequencing and Markov Model methods for predicting high- achieving students (academic and non-academic), the following hypothesis tests were conducted:

a. Hypothesis 1: The pattern of changes in GPA from semester to semester and student participation in non-academic activities (organizations, competitions, seminars) influences the accuracy of predictions using the Sequencing and Markov Model methods. The results of the hypothesis test show that data from 100 students with GPA, organization, competition, and seminar indicators produced different predictions by the two methods. The Sequencing method successfully detected a consistent pattern of improvement in achievement, especially among students who were active in non-academic activities, while the Markov Model was more sensitive to transitions in grades between semesters without considering the additional context of student activities.

b. Hypothesis 2: The Sequencing method is more effective than the Markov Model in predicting high-achieving students.

   The test results show that Sequencing produced a prediction accuracy of 47%, while the Markov Model only achieved 73%. This indicates that the Sequencing method is significantly more accurate in recognizing the academic and non-academic patterns of high-achieving students, particularly because it considers sequence patterns rather than just the probability of transitions between grade statuses.

c. Hypothesis 3: There is a significant difference between the prediction results of high-achieving students using the Sequencing method and the Markov Model.

Based on the classification results:

The Sequencing method successfully predicted 47 out of 100 students according to their original labels. The Markov Model method only successfully predicted 73 students correctly. The prediction difference of 18% reflects a statistically and practically significant difference between the two methods. Therefore, it can be concluded that Sequencing is superior overall compared to Markov in the context of predicting high-achieving students based on longitudinal academic data and non-academic

3.5 Discussion

This study aims to compare the effectiveness of the Sequencing and Markov Model methods in predicting high-achieving students based on academic and non-academic indicators. Empirically, the Markov Model demonstrated higher accuracy and precision (73% and 70.97%) compared to Sequencing (47% and 44.21%), but both Sequencing and Markov had the same recall rate (100%), indicating greater sensitivity in identifying high-achieving students. Theoretically, this is due to the Sequencing approach, which considers the cumulative historical development of grades and non-academic activities, while Markov only focuses on transitions between semesters. Based on these results, it can be concluded that transition- based prediction models are superior in targeted classification, while historical trace-based models are stronger in comprehensive detection. These findings align with previous studies such as Setiawan et al. (2022) and Lestari & Nugroho (2021), which emphasize the advantages of the longitudinal approach, and support Nugraha's (2020) research on the effectiveness of Markov for short-term prediction. Therefore, the selection of prediction methods should be tailored to the context and objectives, and an integrative approach combining the strengths of both methods could be an ideal solution in the future.

4. CONCLUSION

Based on the results of the analysis and discussion of the data, the author draws the following conclusions from the study comparing the Sequencing and Markov Model methods in prediction. The Markov Model method demonstrated superior performance, with an accuracy of 73%, precision of 70.97%, recall of 100%, and an F1-score of 82.98%, compared to the Sequencing method, which achieved an accuracy of 47%, precision of 44.21%, recall of 100%, and an F1-score of 63.30%. The Sequencing method excels in recall (100.00%), meaning it can identify all high-achieving students without any omissions. However, this method has a weakness in low precision (44.21%), indicating a tendency for the model to predict almost all students as high-achieving, resulting in many false positive classifications. This results in lower accuracy (47.00%) and F1-Score (61.26%) values for the Sequencing method compared to other methods such as Markov. The Markov Model is more effective in capturing the transition patterns of GPA values between semesters, thereby providing more accurate and statistically balanced predictions. Based on the hypothesis test, the alternative hypothesis is accepted, which states that the Markov Model is more effective and accurate than Sequencing in the context of predicting high-achieving students. The 25% difference in prediction results between the two methods confirms that the probabilistic approach based on transition states (Markov) is more appropriate for longitudinal academic data. Further research is recommended to develop a hybrid approach that combines the strengths of Markov and Sequencing to produce more comprehensive predictions of student performance. Additionally, it is important to incorporate additional variables such as motivation, learning interest, and environmental factors to enrich the predictive model. For higher education institutions, the application of this predictive method can assist in the identification and development of high-achieving students in a more accurate and objective manner. Campuses can utilize this model in scholarship allocation, student potential mapping, and the planning of performance development programs that encompass both academic and non- academic aspects.

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