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IT CAREER NAVIGATION: PERFORMANCE EVALUATION OF KNN AND NAÏVE BAYES IN CAREER PATH RECOMMENDATIONS FOR COMPUTER SCIENCE STUDENTS (CASE STUDY: BATTUTA UNIVERSITY)

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Abstract: *With the rapid development of information technology, there are many career options available in the field of informatics. However, it is often difficult for students to choose a specialization that matches their interests and abilities. The purpose of this study is to develop a career path recommendation system for informatics students and to evaluate the performance of the K-Nearest Neighbor (KNN) and Naive Bayes algorithms in classification tasks. The data used in this study were collected via a questionnaire comprising 22 assessment indicators related to students' interests, academic understanding, and preferred work styles. A total of 300 respondent data points were utilized, with 20% allocated for testing and 80% for training. The research process included preprocessing, data transformation, modeling, and evaluation using accuracy, precision, recall, and F1-score metrics. The results show that the Naive Bayes algorithm outperforms KNN, achieving an accuracy of 97%, precision of 93%, recall of 93%, and an F1-score of 93%. Therefore, Naive Bayes is considered more optimal in terms of classification performance. It is expected that the developed system can assist students in determining their career paths in a more data-driven and objective manner.*

Keywords: *Machine Learning, KNN, Naïve Bayes, Career Recommendation, Classification*

Abstrak: Dengan berkembangnya teknologi informasi yang cepat, ada banyak pilihan karir di bidang informatika. Namun, sulit bagi mahasiswa untuk memilih spesialisasi yang sesuai dengan minat dan kemampuan mereka. Tujuan dari penelitian ini adalah untuk membuat sistem rekomendasi jalur karier untuk mahasiswa informatika dan juga untuk mengevaluasi bagaimana algoritma K-Nearest Neighbor (KNN) dan Naive Bayes bekerja dalam klasifikasi. Data yang digunakan diperoleh melalui kuesioner yang terdiri dari 22 indikator penilaian yang berkaitan dengan minat mahasiswa, pemahaman akademik, dan gaya kerja yang mereka sukai. Sebanyak 300 data dari responden digunakan, dengan 20% data dialokasikan untuk pengujian dan 80% untuk pelatihan. Proses penelitian termasuk tahapan preprocessing, transformasi data, pemodelan, dan evaluasi menggunakan metrik akurasi, presisi, recall, dan skor F1. Hasil penelitian menunjukkan bahwa algoritma Naïve Bayes lebih baik dibandingkan KNN dengan nilai akurasi 97%, presisi 93%, recall 93%, dan skor F1. Akibatnya, Naïve Bayes lebih optimal dalam member. Diharapkan sistem yang dibuat dapat membantu mahasiswa dalam menentukan karir mereka secara lebih berbasis data dan objektif.

Kata Kunci: Machine Learning, KNN, Naïve Bayes, Rekomendasi Karier, Klasifikasi

INTRODUCTION

The rapid development of

information technology has led to the emergence of many specializations in the tech world, such as computer science, data science, artificial intelligence, network security, and UI/UX design. (Ahmed, 2024), (Shete, 2023), (Samtani et al., 2020), (Samtani et al., 2020), (Oladipo et al., 2024), (Majumder & Veilleux, 2022), (Palmer et al., 2024).

Although these fields offer many career opportunities, Computer Science students must have clear goals and skills from the start. Students are not only expected to understand fundamental concepts such as programming, data structures, databases, and computer networks, but are also expected to determine a specialization path that aligns with their interests, abilities, and industry needs.

However, many computer science students face real-world challenges in determining what career they want. This is due to the extremely broad scope of the discipline, a lack of understanding regarding their own competency profiles, and a lack of support systems that can provide adequate guidance. As a result, students often choose courses or capstone projects without considering whether they align with their abilities or the needs of the job market. This situation can lead to a mismatch between graduates' skills and industry needs, which can result in longer job search times.

Students in the Computer Science Program at Battuta University also face this issue. Initial observations indicate that some students remain uncertain about the specific area of expertise they wish to pursue. Career path selection is typically based on trends or environmental influences, rather than data analysis reflecting students' interests and academic abilities. Therefore, a data-driven, targeted, and objective system is needed to assist students in choosing their careers.

Machine learning is one method that can be used to address this issue during the development of career recommendation systems. (Journal, 2024), (Khare, 2024), (Majjate et al., 2023), (Anand et al., 2024).

Machine learning enables the system to learn patterns from student data, including interests, level of understanding of the material, and academic tendencies, so that it can make more accurate and personalized recommendations. (Kamal et al., 2024), (Lapan et al., 2012), (Gedrimiene et al., 2023), (Bello & Abdallah, 2024). Classification algorithms are suitable tools for predicting students' career paths in such situations. (Choudhari et al., 2024), (Mahboob et al., 2023), (Vellingiri & Venkatesh, 2025).

A crucial first step is to analyze students' competency profiles and interests at Battuta Informatics University. This is achieved through the use of questionnaire data containing twenty-two assessment indicators covering algorithm comprehension, networking, user interface/UX, and work style preferences. A recommendation system model is also used to build a career prediction model. Machine learning methods are used to categorize students into specific fields of expertise, such as computer science, data science and artificial intelligence, network security, information systems, and UI/UX.

The two most commonly used classification algorithms are K-Nearest Neighbor (KNN), which operates based on the proximity of distances between data points; Naive Bayes, on the other hand, uses a probabilistic approach based on Bayes' theorem, and is very simple and effective in handling classification data (Choudhari et al., 2024), (Vellingiri & Venkatesh, 2025), (Khan et al., 2023), (Çetinkaya et al., 2023).

Since each algorithm has its own strengths and weaknesses, a performance evaluation is necessary to determine which method is most effective for making career path recommendations for students.

This study aims to develop a career path recommendation system for

computer science students by comparing the performance of the K-Nearest Neighbor and Naive Bayes algorithms. This case study was conducted on students at Battuta University to create a model that aligns with current data. It is hoped that the results of this study will help students choose better careers and improve the quality of graduates to meet industry demands.

RESEARCH METHODOLOGY

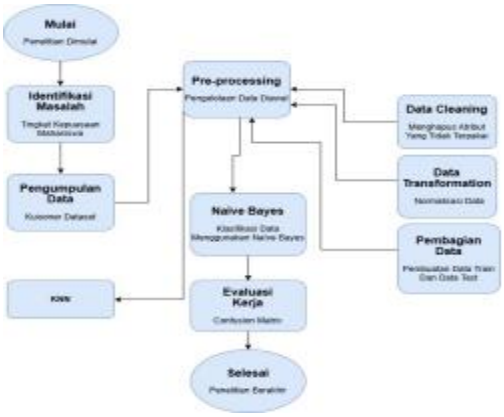

Figure 1 Research Methodology Flowchart

This research method uses the K-Nearest Neighbor (KNN) and Naive Bayes algorithms to build and evaluate a career path recommendation system for computer science students. The research method diagram illustrates the research process flow, which begins with problem identification and concludes with the generation of data-driven career recommendations. This process is described as follows:

Problem Identification

The objective of this stage is to determine the main problem in the research, namely the difficulty computer science students face in determining a career path that aligns with their interests and competencies. Additionally, the literature is reviewed to gain an understanding of the concepts of recommendation systems, machine learning, and the algorithms to be used.

Data Collection

Computer Science students at Battuta University were given a questionnaire to collect research data.

1. Level of academic understanding (algorithms, programming, databases, networks, and so on).
2. Interest in specific IT fields
3. Preferred work style (analytical, creative, technical, etc.).
4. This questionnaire consists of 22 assessment indicators that represent students' competency profiles and interests.

1. Data Preprocessing

The process of preparing this data before using it in a machine learning model consists of two stages:

1. Data Cleaning: Removing incomplete or invalid data
2. Data Transformation: Converting qualitative data into numerical values (encoding)
3. Data Normalization: Ensuring the data scale is unbiased
4. Data Split: Dividing the dataset into training and testing data.
5. The primary goal of this stage is to produce a clean dataset ready for processing.

2. Student Profile Analysis

At this point, the data is explored to understand student characteristics, namely:

1. Identifying patterns of student interest in specific topics
2. Analyzing their level of understanding of education based on metrics.
3. Organizing students' initial tendencies.
4. The results of this analysis are used as the basis for the classification process and help improve the model's accuracy.

3. Model Development (Modeling)

This stage is the core of the research, namely building a classification model using two algorithms. The first algorithm

is K-Nearest Neighbor (KNN). This algorithm classifies data based on distance from other data, using the K parameter (number of nearest neighbors). This algorithm is suitable for data based on similarity patterns.

The second algorithm, Naive Bayes, takes a probabilistic approach based on Bayes' Theorem, assuming that features are independent. It is efficient for data with a high number of dimensions: The model is trained to identify patterns of relationships between student profiles and career paths using training data.

Model Testing (Validation)

The trained model is then tested with test data to:

1. Evaluate the model's predictive ability on new data.
2. Determine whether the classification results from this stage are consistent with the predicted student career paths.

Purpose of Performance Evaluation

This stage is to compare the performance of the KNN and Naïve Bayes algorithms using evaluation metrics such as accuracy:

1. Accuracy: The degree of accuracy in predictions
2. Precision: Accuracy in positive classifications
3. *Recall:* The ability to identify relevant data
4. *Confusion Matrix:* A visualization of the classification results used to determine the most optimal algorithm.

4. Results and Recommendations

5. The Final Stage includes:

1. Determining the most suitable algorithm based on evaluation results
2. Providing a system that recommends career paths for students, covering several fields of specialization, namely software engineering; data science/artificial intelligence; networking and security; UI/UX design; and information systems.
3. It is hoped that this system can help students determine their career paths in a more structured, data-driven, and objective manner.

RESULTS AND DISCUSSION

Data collection was based on the results gathered from a questionnaire distributed to students in the computer science program at Batutta University in Medan. The questionnaire consisted of statements measuring students' aptitude for various career paths. There were 22 questions to be answered by students on a scale of 1 to 5. The following are the questions used in the questionnaire:

Table 1 Questionnaire Statements

Statement	Description	Rating Scale
Q1	I am interested in learning about application development (web/mobile)	"1-5"
Q2	I am interested in the field of artificial intelligence (AI) and machine learning	
Q3	I am interested in data analysis and processing	
Q4	I am interested in computer networks and system security	
Q5	I am interested in application interface design (UI/UX)	
Q6	I am interested in developing business-based systems (Information Systems)	
Q7	I have a good understanding of Basic/Advanced Programming courses	
Q8	I have a good understanding of the Data Structures course	
Q9	I have a good understanding of the	

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	Database course
Q10	I understand the Computer Networks course
Q11	I understand the Data Mining / Machine Learning course
Q12	I understand the Human-Computer Interaction (UI/UX) course
Q13	I am able to create web-based applications independently
Q14	I am able to analyze data using tools (Excel/Python/etc.)
Q15	I am able to create simple machine learning models
Q16	I understand the concept of computer networks and basic configuration
Q17	I am able to create an attractive application UI design
Q18	I have strong problem-solving skills in programming
Q19	I prefer logic-based work over visual work
Q20	I prefer analyzing data to building applications
Q21	I prefer working in a team rather than individually
Q22	I prefer technical work over managerial work
Recommendations	Recommendation results

In Table 1 of the questionnaire, columns Q1 through Q22 contain statements for each variable on the questionnaire form. To obtain the skill recommendation results, Software Engineering skills depend on the scale values of statements Q1,Q7, Q8, Q13, Q18, Q19, and Q22; Data Science/AI expertise depends on the scale values of statements Q2, Q3, Q11, Q14, Q15, and Q20; and Network & Security expertise depends on the scale values of statements Q4, Q10, Q16, Q19, and Q22; UI/UX expertise depends on the scale values of statements Q5, Q12, Q17, and Q21; and Information Systems expertise depends on the scale values of statements Q6, Q9, and Q21.

After the questionnaire was distributed to the respondents—computer science students—a total of 300 data points were successfully collected. The data was obtained from sixth-semester computer science students. This data will be processed according to the research method described earlier, and the respondents' data will be presented as follows:

Table 2 Questionnaire Content

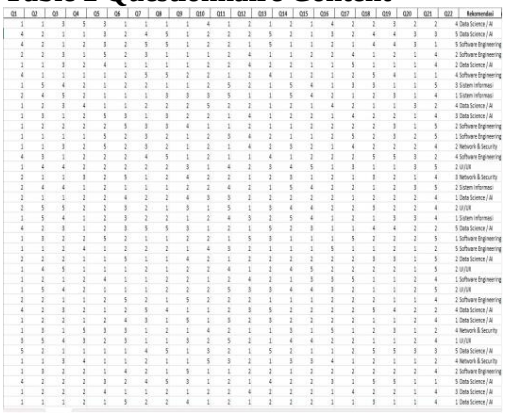

Table 3. Table of Recommendation Results

Value	Recommendation Results	Source of Statement
1	Software Engineering	Q1, Q7, Q8, Q13, Q18, Q19, Q22
2	Data Science / AI	Q2, Q3, Q11, Q14, Q15, Q20
3	Network & Security	Q4, Q10, Q16, Q19, Q22
4	UI/UX	Q5, Q12, Q17, Q21
5	Information Systems	Q6, Q9, Q21

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The values for these recommendation variables were obtained from measurements of the average results for each recommendation variable, such as Software Engineering, using the average value of the source statements. The following table shows the average calculations:

Table 4 Table of Average Calculations for Recommendation Results

=AVERAGE(A2;G2;H2;M2;R2;S2;V2)

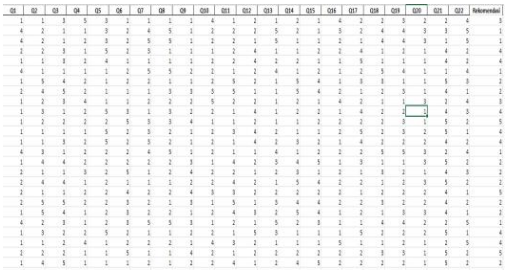
	W	X	Y	Z	AA	AB	AC	AD
	Rekomendasi	mendasi dalam angka		1 Software Eng	2 Data Science	3 Network	4 UI/UX	5 SI
4	Data Science / AI	3		1,857142857	1,666666667	4,0000	2,2500	1,33333
5	Data Science / AI	1		4,428571429	1,833333333	2,7500	2,5000	2
5	Software Engineering	1		4,571428571	1,666666667	2,7500	1,5000	1,33333
2	Software Engineering	4		1,714285714	1,833333333	1,5000	4,2500	2,33333
2	Data Science / AI	4		1,285714286	1,666666667	1,7500	4,2500	2
4	Software Engineering	1		4,428571429	1,166666667	2,0000	1,5000	1,66667
3	Sistem Informasi	2		1,714285714	4	2,0000	2,7500	2,66667
1	Sistem Informasi	2		1,857142857	4	2,0000	1,7500	2,66667
4	Data Science / AI	3		1,714285714	2,166666667	4,2500	1,7500	1,66667
3	Data Science / AI	4		1,857142857	1,666666667	2,0000	4,2500	3
2	Software Engineering	5		2,142857143	1,5	1,7500	2,7500	4,66667
1	Software Engineering	4		2	1,5	1,5000	4,7500	2,66667
2	Network & Security	4		2	2	1,7500	4,2500	2,33333
4	Software Engineering	1		4,428571429	1,833333333	2,5000	1,7500	1,66667
2	UI/UX	2		1,714285714	4	1,5000	3,0000	3,33333
3	Network & Security	2		2,142857143	1,5	2,5000	2,0000	4,33333
2	Sistem Informasi	2		1,428571429	4	1,7500	2,7500	2,66667
1	Data Science / AI	5		1,857142857	1,833333333	2,0000	2,2500	4
2	UI/UX	2		2,142857143	4,166666667	1,7500	2,2500	3,33333
1	Sistem Informasi	2		1,714285714	4,166666667	1,2500	2,7500	2,66667
5	Data Science / AI	1		4,571428571	2,333333333	2,0000	1,5000	2,66667
1	Software Engineering	4		1,571428571	1,666666667	1,5000	5,0000	3
5	Software Engineering	4		2	1,5	4,5000	1,5000	1,66667
2	Data Science / AI	5		2	1,666666667	1,7500	2,5000	4,66667
2	UI/UX	2		1,714285714	3,833333333	1,7500	2,2500	2,66667
1	Software Engineering	4		1,285714286	1,833333333	1,7500	4,2500	2,33333
2	UI/UX	2		1,571428571	4	2,2500	2,7500	2,66667
2	Software Engineering	5		1,571428571	1,333333333	1,7500	2,5000	4,66667
4	Data Science / AI	1		4,428571429	2,166666667	2,2500	2,0000	1,66667
1	Data Science / AI	5		1,571428571	2,166666667	1,2500	2,5000	4,33333
4	Network & Security	3		2	1,833333333	4,5000	1,7500	2
1	UI/UX	2		1,285714286	4	2,0000	2,5000	3,33333
5	Data Science / AI	1		4,857142857	1,833333333	2,5000	1,7500	1,66667
4	Network & Security	3		1,714285714	2,333333333	4,2500	1,5000	1,33333
2	Software Engineering	5		1,714285714	1,833333333	1,7500	2,2500	4,33333
5	Data Science / AI	1		4,571428571	1,833333333	2,7500	1,5000	2
3	Data Science / AI	4		1,857142857	1,833333333	2,0000	4,0000	2
1	Data Science / AI	5		1,714285714	1,5	1,2500	1,7500	4,33333

Pre-processing

In this stage, the data will be processed to ensure it is of good quality and can be processed by the Python system to determine the accuracy of the KNN and Naive Bayes methods.

The data cleaning process in this stage aims to minimize unused data or attributes. As shown in Table 2, the recommendation attributes—which were originally text data—will be converted into numerical data as follows:

Table 5 Recommendation Data Transformation



Next, the data is divided into two parts: training data and test data, derived from the X and Y values. Thus, X is split into X_train and X_test, and Y is split into Y_train and Y_test. Of the 300 data points, 80 percent constitute the training data and 20 percent the test data.

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Data Modeling

The next step is data modeling. After the data has undergone data cleaning, data transformation, and data splitting, it is then processed using the KNN and Naïve Bayes algorithms.

```
==== K-Nearest Neighbors ====
Accuracy   : 0.9333
Precision   : 0.9442
Recall     : 0.9333
F1-Score   : 0.9334

Classification Report:
              precision    recall  f1-score   support

           1       0.82      1.00      0.90        14
           2       0.88      1.00      0.93         7
           3       1.00      0.88      0.94        17
           4       1.00      1.00      1.00        12
           5       1.00      0.80      0.89        10

    accuracy                           0.93        60
   macro avg       0.94      0.94      0.93        60
weighted avg       0.94      0.93      0.93        60
```

Figure 2 KNN Algorithm Results

```
==== Naive Bayes ====
Accuracy   : 0.9667
Precision   : 0.9699
Recall     : 0.9667
F1-Score   : 0.9665

Classification Report:
              precision    recall  f1-score   support

           1       0.93      1.00      0.97        14
           2       0.88      1.00      0.93         7
           3       1.00      0.88      0.94        17
           4       1.00      1.00      1.00        12
           5       1.00      1.00      1.00        10

    accuracy                           0.97        60
   macro avg       0.96      0.98      0.97        60
weighted avg       0.97      0.97      0.97        60
```

Figure 3 Naïve Bayes Algorithm Results

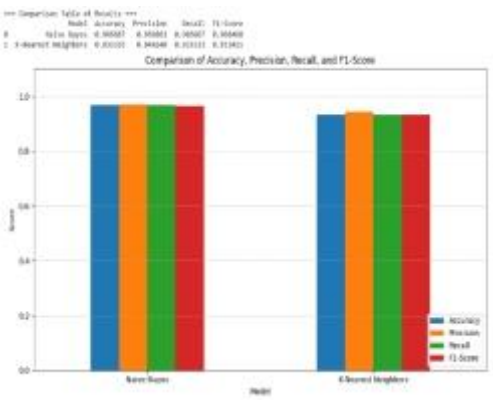

Figure 4 Comparison Chart

KNN and Naïve Bayes Algorithms

The results obtained from the calculation process using Python on the Google Colab platform show that the KNN algorithm achieved an accuracy of 93%, precision of 94%, recall of 93%, and an F1-Score of 93%, while the Naïve Bayes algorithm achieved an accuracy of 97%, a precision of 97%, a recall of 97%, and an F1-Score of 97%. The Naïve Bayes algorithm demonstrated better accuracy, precision, recall, and F1-Score values compared to the KNN algorithm.

CONCLUSION

Based on the research conducted, it can be concluded that a machine learning-based career path recommendation system can help Computer Science students obtain more structured and objective career guidance. The analysis process can more systematically describe students' interest and competency profiles through questionnaire data containing 22 indicators.

The evaluation results show that the Naïve Bayes algorithm achieves higher accuracy, precision, recall, and F1 scores than the K-Nearest Neighbor (KNN) algorithm in classifying students' career paths. Therefore, the Naïve Bayes algorithm is recommended as a superior method for developing a student career recommendation system.

Overall, this study demonstrates that the use of machine learning can help students find career paths that align with their interests and abilities. The system can also improve the quality of graduates to better meet industry demands.

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