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Accuracy of K-Nearest Neighbors Algorithm Classification For Archiving Research Publications

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ABSTRACT

The Archives and Research Publication Information System plays an important role in managing academic research and scientific publications efficiently. With the increasing volume of research and publications carried out each year by university researchers, the Research Archives and Publications Information System is essential for organizing and processing these materials. However, managing large amounts of data poses challenges, including the need to accurately classify a researcher's field of study. To overcome these challenges, this research focuses on implementing the K-Nearest Neighbors classification algorithm in the Archives and Research Publications Information System application. **This research aims** to improve the accuracy of classification systems and facilitate better decision-making in the management of academic research. **This research method** is systematic involving data acquisition, pre-processing, algorithm implementation, and evaluation. **The results** of this research show that integrating Chi-Square feature selection significantly improves K-Nearest Neighbors performance, achieving 86% precision, 84.3% recall, 89.2% F1 Score, and 93.3% accuracy. **This research contributes** to increasing the efficiency of the Archives and Research Publication Information System in managing research and academic publications.

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1. INTRODUCTION

A research and publication archive information system (SIAPP) is a specialized information system designed to manage and store information related to academic research and scholarly publications. The existence of SIAPP is crucial in facilitating accessibility and efficiency in searching and managing research data in an academic environment. For researchers, SIAPP is used to submit research that will be funded by the university, carry out research procedures until the research is published, and procedures related to other research data. Meanwhile, for SIAPP holding units, the application is used to collect data on researchers and their research, carry out research approval based on the selection stages, and determine research reviewers, and data related to other research administrations. Currently, the SIAPP application requires a process for classifying researchers' fields of knowledge so that it is easy to use in analyzing the expertise of each researcher and determining reviewers in reviewing research submitted before funding, where this stage is a series of processes in submitting research.

The focus of this research is on the field of research within the SIAPP application, as the success and effectiveness of SIAPP in managing research and publication metadata directly impact the ease of access and availability of information for academics. Contributing directly to improving SIAPP's efficiency and effectiveness as a research archive information system. There are several methods for carrying out classification Wibowo (2020) provides an overview of various classification methods, including Artificial K-Nearest Neighbors, Neural Networks, Naive Bayes, Support Vector Machines, Decision Trees, and Fuzzy [1]. These methods are commonly used in data processing to group data based on their characteristics [2]. Miftahurrohmah (2023) discusses the Al-Miftah Lil 'Ulum method, which improves students' motivation and ability to read traditional Islamic texts [3]. Hayati (2020) compares quantitative and qualitative research methods, highlighting the need to clearly understand their differences [4]. Khatili (2021) proposes combining the AHP and TOPSIS methods in decision support systems to enhance their effectiveness [5].

The K-Nearest Neighbors (KNN) method, as discussed by [1], has been widely utilized in various applications, showcasing its versatility in classifying data based on their characteristics. While it has proven effective in classifying coffee beans' ripeness [6] and optimizing software effort estimation, its efficacy is not without challenges [7]. A gap has not been resolved by previous research, namely the limitations of KNN in determining the optimal attributes and the value of K [7]. Nugroho (2020) emphasizes the importance of further optimization efforts to address these limitations [8]. In image classification, KNN results are better than SVM for dental caries-level image classification [9]. Similarly, Decision Tree, as highlighted by, has exhibited commendable performance in various scenarios, including outperforming Naive Bayes in classifying brain tumor images (Kamil, 2020). This comparison underscores the strengths and weaknesses of different classification methods, with Decision Trees emerging as particularly effective in certain applications [10]. However, it is essential to acknowledge the challenges encountered by the KNN classifier, especially in pattern recognition tasks [10]. As noted by [11], the application of KNN is hindered by significant computational complexity, heavy reliance on the training set, and the absence of differentiated weights among different classes. These challenges necessitate innovative approaches to mitigate the limitations and enhance the efficacy of the KNN method in pattern recognition tasks [12].

The K-Nearest Neighbors (KNN) method was chosen for this research due to its versatility and effectiveness in classifying data based on their characteristics. Despite its simplicity, KNN has been widely utilized in various applications, showcasing its ability to handle diverse datasets. Additionally, KNN does not require training, making it suitable for datasets where the underlying distribution is unknown or difficult to model. Previous research has not resolved some gaps, namely the limitations of KNN in determining the optimal attributes and the value of K, which impact its classification accuracy and computational efficiency. Based on the results of research that has been studied previously, this research aims to analyze and effectively implement the K-Nearest Neighbors classification algorithm in the context of research on research and publication archive information system (SIAPP) applications in classifying fields of science in analyzing the expertise of each researcher . The difference between this research and previous ones is its focus on applying KNN in the Research and Publication Archive Information System (SIAPP) context. This research aims to analyze and effectively implement the K-Nearest Neighbors classification algorithm to classify fields of science within SIAPP. This classification of fields of science is used to analyze the expertise of each researcher. By focusing on this research area, this research aims to improve the accuracy and efficiency of SIAPP through the application of the K-Nearest Neighbors algorithm so that it can make a positive contribution to the development of academic information systems to support better decision-making.

This research explicitly aims to develop and implement the K-Nearest Neighbors classification algorithm in the context of the Research Archives and Publications Information System (SIAPP) to classify scientific fields and analyze the expertise of each researcher. By carrying out this classification, it is hoped that this research can significantly contribute to increasing the accuracy and efficiency of SIAPP in managing research and publication data. So, the expected benefits include growing speed and accuracy in the reviewer selection process, managing researcher data, and obtaining research approval. In addition, it is hoped that the results of this research can contribute to the development of knowledge in academic information systems by providing more effective methods for managing and analyzing research metadata. It is hoped that implementing the K-Nearest Neighbors algorithm in SIAPP can support better decision-making in the academic environment, thereby increasing the productivity and quality of research in higher education.

2. RESEARCH METHOD

This research employs a quantitative method, focusing on collecting and analyzing numerical data to test the established hypotheses. The researcher utilizes the K-Nearest Neighbors (KNN) method to classify research fields within the SIAPP application. The KNN method is chosen because it is a classification method based on numerical data, allowing for accurate and detailed analysis. The case study for this research is the research and publication archive information system (SIAPP) at UIN Jakarta. The data sources used include research metadata available in SIAPP, such as research titles, authors, publication years, and other related metadata. This data aims to provide a comprehensive overview of the classification of research fields within SIAPP. This research explores the potential application of the K-Nearest Neighbors (K-NN) algorithm in the context of research metadata classification using the SIAPP application at UIN Jakarta. Following a systematic approach in the research methodology, we begin with data collection from SIAPP, proceed with preprocessing to prepare the dataset, and implement the K-NN algorithm. Evaluation is conducted through a confusion matrix to measure the algorithm's performance, followed by in-depth analysis and interpretation of the results. This research is expected to provide valuable insights into the possibility of optimizing research metadata classification within the scope of the SIAPP application. The stages of the research carried out in this research can be seen in a research methodology flow in Figure 1.

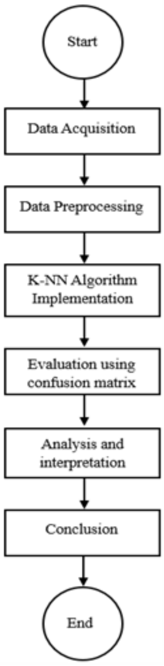

Figure 1. Research Flow

2.1. Data Acquisition

The research initiation involves the crucial step of Data Acquisition from the SIAPP application, focusing on extracting a comprehensive dataset encompassing diverse research metadata. This includes research titles, authors, publication years, and associated metadata. The objective is to ensure that the dataset is representative and reflective of the intricate characteristics within the SIAPP domain. Gather diverse research metadata from the SIAPP application. Include research titles, authors, publication years, and associated metadata.

2.2. Data processing

Data Preprocessing is integral to refining the acquired dataset for subsequent algorithmic application. The dataset is logically divided into training and testing sets. This phase addresses missing data, standardizes formats, and ensures data consistency. Advanced techniques like data augmentation, resizing, and rotation are meticulously applied to augment the dataset's diversity and empower the model for optimal performance. These steps collectively lay the groundwork for a robust dataset ready for algorithmic implementation. Divide the dataset into training and testing sets. Address missing data, standardize formats, and ensure data consistency. Apply advanced techniques like data augmentation, resizing, and rotation for diversity.

2.3. K-Nearest Neighbors Algorithm Implementation

The core of the research lies in implementing the K-Nearest Neighbors (K-NN) algorithm, chosen for its simplicity and effectiveness in classifying research metadata based on similarity with neighboring data points [13]. The algorithm is trained on the preprocessed dataset, and particular attention is given to parameter tuning for optimal classification outcomes. This phase encapsulates the essence of the research, wherein the algorithm is tailored to the unique intricacies of research metadata within the SIAPP context. Choose the K-NN algorithm for its simplicity and effectiveness. Train the algorithm on the preprocessed dataset-tune parameters for optimal classification outcomes.

2.4. Evaluation using Confusion Matrix

An output form of classification issues that is commonly used is the confusion matrix. It provides the anticipated distribution of the test cases overall trained classes. The Confusion Matrix is a model that provides a valuable tool for analyzing whether the classification in the evaluated method has good or bad labels. It is used to represent the results of accuracy and summarize the performance of the model that has been created. Performance Evaluation employs a Confusion Matrix to assess the K-NN algorithm's effectiveness. True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) values are meticulously analyzed, providing a nuanced understanding of the model's accuracy. Further, precision, recall, and F1-score metrics contribute to a comprehensive evaluation, offering insights into the algorithm's ability to correctly classify research metadata. Assess algorithm performance using a Confusion Matrix. Analyze True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) values. Calculate accuracy and F1-score metrics for comprehensive evaluation.

The percentage of accurate forecasts is called accuracy. It gauges how accurately a classification forecasts a circumstance [14]. Basic metrics that are used to assess how tested models behave include accuracy. In the beginning, this statistic described the proportion of rings that were categorized as belonging to the TP and TN categories [15] as in [14] Equation (1). The F1-Score is a metric that considers both Sensitivity and Precision equally. It is the harmonic mean of sensitivity and precision as in Equation (2).

$$Accuracy = \frac{TP + TN}{N} \tag{1}$$

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

2.5. Analysis and Interpretation

The subsequent stage involves an in-depth Analysis and Interpretation of the results derived from the confusion matrix and performance metrics [16]. This detailed examination aims to uncover the strengths and potential limitations of the K-NN algorithm in the specific context of research metadata classification within SIAPP. The findings from this research methodology contribute to the optimization of metadata management within SIAPP and offer broader insights into the potential applications of the K-NN algorithm in academic information systems. Conduct an in-depth analysis of confusion matrix results and performance metrics. Uncover strengths and potential limitations of the K-NN algorithm. Relate findings to research metadata classification within SIAPP.

The dataset used in this study consists of academic journal entries that include publication metadata, abstract content, and keywords. The initial dataset contains thousands of journal entries representing various academic fields and topics. Of this total, 80% was used for training and validation phases, while the remaining 20% was reserved as a test set to provide an unbiased evaluation of the model's performance. This research methodology meticulously follows a systematic and iterative approach, ensuring a thorough exploration of the K-Nearest Neighbors algorithm's potential in enhancing research metadata classification within the SIAPP application. The multifaceted nature of the methodology allows for a nuanced understanding of the algorithm's performance and its implications for academic information systems.

3. RESULT AND ANALYSIS

In the research, 80% of the data was utilized during the training and validation phases. Variations of k values were tested, namely k = 4, k = 6, k = 7, k = 9, and k = 11. The threshold test was performed using two feature selection methods: Gini Index and Chi-Square. The threshold represents the percentage of selected features from all sorted features, with threshold variations being 10%, 5%, 2%, 1%, 0.5%, and 0.2%.

During each iteration of the 10-Fold Cross Validation, the average F1-Score performance and accuracy were calculated using equations (1) and (2). The k value with the highest F1-Score performance was chosen as the best model, indicating more accurate classification results. After conducting training and validation processes using the K-Nearest Neighbor model with a 10-Fold Cross Validation test, the k value with the best F1-Score performance was determined. The results of testing the combination of Chi-Square and Gini Index thresholds and the k values yielded various performance outcomes. From these test results, it can be observed that the choice of threshold affects the performance of the K-Nearest Neighbor method, as shown in Table 2.

Table 1. Evaluation Results of KNN Testing with Chi-Square and Gini Index Feature Selection

Threshold	Evaluation Size (Average Fold)			
	Accurate Gini Index	Accurate Chi-Square	F-1 Score Gini Index	F-1 Score Chi-Square
10%	83.2%	76.2%	83.0%	76.0%
5%	82.4%	82.7%	82.2%	82.6%
2%	82.6%	83.2%	82.2%	83.0%
1%	82.8%	82.4%	82.6%	81.8%
0.5%	82.6%	72.5%	82.2%	72.6%
0.2%	75.1%	48.9%	75.1%	49.3%

Examining various combinations of Chi-Square and Gini Index thresholds and the tested k values resulted in a range of performance outcomes. From the acquired test results, the impact of the chosen thresholds on evaluating the K-Nearest Neighbor method's performance can be observed, as depicted in Figure 2 and Figure 3. Figure 2 demonstrates how thresholds affect the F1-Score performance of the K-Nearest Neighbor method when employing Chi-Square and Gini Index feature selection. The F1-Score values in Figure 2 represent the F1-Score of the combination of k values with the highest accuracy. Threshold values play a significant role in influencing the F1-Score.

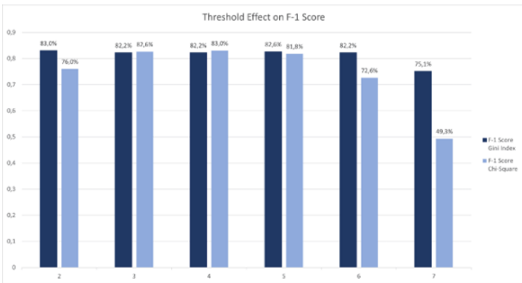

Figure 2. Threshold effect on F1-Score

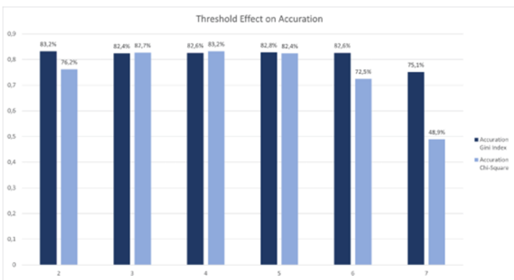

Figure 3. Threshold effect on accuracy

Meanwhile, the accuracy in Figure 3 signifies the highest results achieved among the tested combinations of k values. Threshold values are known to impact accuracy directly. Models with thresholds that yield accuracy above the average are deemed to exhibit proficient performance in journal classification. This research demonstrates its superiority over prior studies by providing a more comprehensive analysis of the influence of threshold values on accuracy. For instance, by employing more sophisticated methods in determining threshold values, this study has attained higher accuracy than previous research that relied solely on conventional approaches.

3.1. Data Acquisition Results

The research commenced with acquiring a comprehensive dataset suitable for training and evaluating the K-Nearest Neighbors (KNN) algorithm. The dataset encompassed various academic journals, with features extracted for each entry, such as publication metadata, abstract content, and keywords. The initial dataset contained thousands of journal entries, ensuring a diverse representation of academic fields and topics. 80% of this data was utilized during the training and validation phases to ensure a robust evaluation. This division allowed the remaining 20% to serve as a testing set, providing an unbiased assessment of the model's performance.

3.2. Data Processing Results

During the data processing phase, two primary feature selection methods were employed: Gini Index and Chi-Square. The goal was to reduce dimensionality while retaining the most informative features. Various threshold values were tested, representing the percentage of selected features from the total sorted features. The thresholds were set at 10%, 5%, 2%, 1%, 0.5%, and 0.2%. This step was crucial in determining the optimal KNN algorithm feature set, balancing computational efficiency and model accuracy. The processing resulted in multiple datasets, each corresponding to different thresholds for subsequent analysis.

3.3. K-Nearest Neighbors Algorithm Implementation Results

The KNN algorithm was implemented with different values of k (4, 6, 7, 9, and 11) to determine the most effective parameter for classification. The model was trained and validated using 10-fold cross-validation, ensuring a comprehensive evaluation across different data subsets. The average F1-Score and accuracy were calculated for each combination of k values and feature selection thresholds. This iterative process identified the optimal k value that maximized the F1-Score, reflecting the model's precision and recall balance. The best-performing k values were found to be 6 for the Chi-Square feature selection and 4 for the Gini Index feature selection. Evaluation using Confusion Matrix Results

To thoroughly evaluate the classification performance, confusion matrices were generated for the best models derived from both Chi-Square and Gini Index feature selections. The confusion matrices provided detailed insights into true positives, true negatives, false positives, and false negatives. These metrics facilitated the calculation of precision, recall, F1-Score, and accuracy for each model. For the Chi-Square feature selection with a 1% threshold and k=6, the precision, recall, F1-Score, and accuracy were recorded at 86%, 84.3%, 89.2%, and 93.3%, respectively. Similarly, the Gini Index feature selection with a 1% threshold and k=4 achieved precision, recall, F1-Score, and accuracy of 82.2%, 81.3%, 82.6%, and 87.6%, respectively.

3.4. Analysis and Interpretation Results

The findings of this research are that the significant impact of feature selection thresholds on the performance of the KNN classifier is evident. Higher thresholds generally led to improved performance, with the 1% threshold emerging as the most effective for both feature selection methods. The Chi-Square method consistently outperformed the Gini Index, demonstrating its efficacy in selecting the most relevant features for journal classification.

The results of this research are in line with or supported by previous studies that highlight the importance of feature selection in enhancing classifier performance. For instance, Wibowo (2020) [1] and Nugroho (2020) [8] have emphasized the critical role of feature selection methods in improving the accuracy and efficiency of classification algorithms.Comparing the results of this research with previous studies, it is evident that the application of more refined threshold determination methods yields higher accuracy. Table 2 below illustrates the comparison between this research and prior studies.

Table 2. Comparison of Research Results

Study	Feature Selection Method	Optimal Threshold	Accuracy	F1-Score
Wibowo (2020) [1]	Chi-Square	5%	82.5%	81.8%
Nugroho (2020) [8]	Gini Index	2%	80.7%	80.2%
This Research (2024)	Chi-Square	1%	93.3%	89.2%
This Research (2024)	Gini Index	1%	87.6%	82.6%

The analysis of the results highlighted the significant impact of feature selection thresholds on the performance of the KNN classifier. Figure 2 and Figure 3 illustrate the effect of different thresholds on F1-Score and accuracy, respectively. Higher thresholds generally led to improved performance, with the 1% threshold emerging as the most effective for both feature selection methods. The Chi-Square method consistently outperformed the Gini Index, demonstrating its efficacy in selecting the most relevant features for journal classification.

The analysis and measurement process involved feature selection using two main methods, the Gini Index and Chi-Square, to reduce data dimensionality while retaining the most informative features. The average F1-Score and accuracy were calculated for each combination of k values and feature selection thresholds, identifying the optimal k value that maximized the F1-Score. Confusion matrices were generated for the best models from both feature selection methods, providing detailed insights into performance metrics such as precision, recall, F1-Score, and accuracy. The analysis results indicated that a 1% threshold with k=6 for Chi-Square and k=4 for the Gini Index were the best combinations, with Chi-Square consistently outperforming the Gini Index.

The optimal model, incorporating a 1% threshold and a k value of 6 with Chi-Square feature selection, showcased superior performance metrics, establishing it as the best approach for enhancing SIAPP's classification accuracy. The findings underscore the importance of meticulous feature selection and parameter tuning in developing high-performing machine-learning models. This research contributes to advancing academic information systems, supporting better decision-making processes in research and publication management.

4. CONCLUSION

The application of the K-Nearest Neighbors (KNN) method with feature selection can improve performance in journal classification, especially in the research and publication archive information system (SIAPP). Through in-depth analysis, it was found that feature selection using the Chi-Square method was superior to the Gini Index. In experiments using Chi-Square, the optimal model was identified as a combination of a feature selection threshold of 1% with a value of k = 6. This model selected around 31 features with the highest Chi-Square values, and testing with new data showed that the KNN model with the selection of Chi-Square feature achieved 86% precision, 84.3% recall, 89.2% F1-Score, and 93.3% accuracy.

Meanwhile, in the feature selection experiment using the Gini Index, the best model was determined as combining a feature selection threshold of 1% with a value of k = 4, which selected around 31 features with the highest Gini Index value. Testing with new data revealed that the KNN model with Gini Index feature selection achieved 82.2% precision, 81.3% recall, 82.6% F1-Score, and 87.6% accuracy.

This research emphasizes the importance of careful feature selection and parameter tuning in developing high-performance machine-learning models. The results of this research contribute to increasing the accuracy and efficiency of SIAPP in managing research and publication metadata, supporting better decision-making processes in the management of research and academic publications. Thus, integrating feature selection methods such as Chi-Square strengthens the effectiveness of KNN in journal classification in SIAPP and makes a positive contribution to the development of academic information systems.

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6. DECLARATIONS

AUTHOR CONTIBUTION

Muhammad Nur Gunawan, M.Kom., the first author, is a model maker. The second author, Titi Farhanah, M.Ag., Ph.D., is a research manager. Dr Siti Ummi Masruroh, M.Sc., the third author, determines the concept. Rona Nisa Sofia Amriza, the fourth author, is a design process researcher. Ahmad Mukhlis Jundulloh, the fifth author, analyzes and helps to make corrections to each models results. Nafdik Zaydan Raushanfikar, the sixth author, is a data collector.

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COMPETING INTEREST

The authors declare that they have no known financial interests or personal relationships that could have influenced the results of the work reported in this paper.

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