Systematic Literature Review: The Use of the K-Nearest Neighbor Algorithm in Data Classification for Government Policy Optimization

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Abstract

Along with the rapid advancement of technology and the progress of the digital era, the volume of data across various sectors has significantly increased, making it necessary to process this data to support policy optimization. Data processing is essential for simplifying complex data by grouping it according to specific characteristics. K-Nearest Neighbor (KNN) is a widely used classification algorithm in data mining implementation, applying the principle of class determination based on the proximity between data points, calculated using the Euclidean distance metric. In the governmental sector, this algorithm has been utilized to improve the efficiency of public policies and data-driven decision support systems. This study employs a Systematic Literature Review (SLR) to examine the use of the K-Nearest Neighbor algorithm in previous research for classifying government-related data as a foundation for formulating more effective and efficient policies. The information is gathered by collecting references from relevant journals and studies to provide a detailed understanding of the effectiveness of data processing as a means for optimizing government policies and offering well-targeted decision-making recommendations.

Keywords*— Data Mining, K-Nearest Neighbor, Government, Systematic Literature Review, Policy Optimization*

1. INTRODUCTION

The rapid growth of data is closely correlated with the increasing volume and complexity of data, which necessitates the use of appropriate methods for data processing in order to produce information that is both valuable and useful for organizations. One technique that can be applied to achieve this is data mining. Data mining combines various methods such as statistics, machine learning algorithms, and artificial intelligence to analyze data and uncover patterns and relationships between data points. Challenges such as processing complex data with manual systems require the implementation of data mining as a solution.

Large volumes of data can have a positive impact if processed and classified using the right data mining approach to identify data patterns, trends, and interrelationships, which can then be used for formulating effective and targeted policies. This study explores various research related to the application of data mining techniques in data processing and focuses on the implementation of the K-Nearest Neighbor algorithm, one of the classification techniques in data mining, for classifying

data provided by the government. This can serve as a recommendation for data-driven decision-making systems based on historical data. Several metrics such as accuracy, precision, recall, and F1-score are used to evaluate how effectively the algorithm performs.

The development of various classification algorithms has been popularly implemented in previous studies. Some commonly used algorithms for classification include K-Nearest Neighbor, Naïve Bayes, Support Vector Machine, Random Forest, Decision Tree, Logistic Regression, and Artificial Neural Network. The results of the literature review indicate that K-Nearest Neighbor is a suitable method for government data processing.

2. RESEARCH METHODS

This study explores various existing research on the use of the K-Nearest Neighbor algorithm in data classification for government policy optimization and develops a systematic review protocol using the PRISMA (Preferred Reporting Items for Systematic Review and Meta-Analysis) method. The process is classified into four stages: Establishing Eligibility Criteria, Identifying Information Sources, Literature Selection, and Data Collection.

2.1. Article Eligibility Criteria

Determined by the Inclusion Criteria (IC), as follows:

a. IC1: The article must be based on original research written in Indonesian, with a title relevant to the specified keywords.
b. IC2: The article must have been published between the years 2020 and 2025.
c. IC3: The article must aim to analyze the use of the K-Nearest Neighbor algorithm in processing data from other researchers for the optimization of government policies.

2.2. Determining Literature Sources

Literature is searched through online databases such as Google Scholar and Semantic Scholar. In addition to articles that meet the inclusion criteria, other studies related to this research are also explored.

2.3. Literature Selection

a. The initial keyword search includes: “Implementation of Data Mining with K-Nearest Neighbor” and “K-Nearest Neighbor Algorithm in the Government Sector”.
b. The process includes exploring and selecting titles, abstracts, and full articles.
c. Keywords are derived from the previous eligibility search results.
d. Articles that were not eliminated in the previous stage are read either entirely or partially to ensure they meet the criteria for the next review phase.
e. Selected articles are then re-reviewed to obtain relevant studies.

2.4. Data Collection

Data is collected manually by filtering 10,790 total journal articles based on two keyword categories: 8,860 journals under the keyword “Implementation of Data Mining with K-Nearest Neighbor” and 1,930 journals under “K-Nearest Neighbor Algorithm in the Government Sector”. From all the sources and criteria defined, 35 scientific journals were found suitable as potential references based on their titles and abstracts and their relevance to the research question. After further review, only 26 selected articles were deemed eligible and met the criteria for this study.

2.5. Data Item Selection

The data from the selected journal articles were then analyzed in terms of the methods and approaches used, specifically focusing on the identification of the application of the K-Nearest Neighbor algorithm in data classification for the optimization of government policy.

Table 1 Research Question

ID	Research Questions	Background
RQ 1	What types of data classification are used in the selected studies related to the use of the K-Nearest Neighbor algorithm in data classification for government policy optimization?	To identify the types of data classification used in selected studies related to the application of the K-Nearest Neighbor algorithm in data classification for government policy optimization.
RQ 2	What are the main contributions of previous studies to the use of the K-Nearest Neighbor algorithm in government data classification?	To identify the main contributions of previous research to the use of the K-Nearest Neighbor algorithm in government data classification.
RQ 3	Can the K-Nearest Neighbor method be utilized in data classification for the optimization of government policies?	To identify the relevance of the K-Nearest Neighbor method in data classification for the optimization of government policies.

3. RESULTS AND DISCUSSION

This study aims to investigate the approaches used by other researchers in identifying the application of the K-Nearest Neighbor algorithm in data classification for the optimization of government policies. In line with this objective, the research identifies items that can recognize and provide demographic characteristics and literature trends within the "Selected Studies”.

Table 2 Literature Review Results

No	Title	Year	Author	Platform	Contribution
1.	Model [Model]… [1]	2022	Titik Khotiah, et al	Rapid Miner	This study used data from the Class I Correctional Institution in Semarang. The dataset includes inmate remission data for 2018. Algorithm-based classification improves transparency and accuracy of remission and avoids administrative discrepancies.
2.	Sistem [System]… [2]	2023	Aziz Ali Mahendra, et al	PHP dan MySQL	The data used in this study was obtained from the Social Service of Bengkulu City, specifically BPJS Health Aid Recipient (PBI) data, which is a government aid program for the poor. The decision support system helps select BPJS-PBI candidates more efficiently than manual methods.
3.	Penerapan [Application]…[3]	2023	Ilham Luqman Hakim, et al.	Jupyter Notebook	The data was obtained from SATPAS Polresta Manokwari, authorized to issue driver's licenses. KNN can classify license categories based on age and application type. This helps SATPAS manage driver data more efficiently.
4.	Penerapan [Application]…[4]	2023	Aas Nurjanah, Ahmad Rifai	Rapid Miner	The data includes poor residents in Susukan Tonggoh Village, used for poverty alleviation programs. The study achieved 94.67% accuracy in classifying the eligibility of poor citizens.
5.	Klasifikasi [Classification]…[5]	2024	Hanna Syajida, et al	Rapid Miner	A total of 1,530 BPNT recipient records from Beber District were classified using KNN, achieving 93.14% model accuracy. RapidMiner visualizations help policymakers identify patterns based on region and economic category.
6.	Analisis [Analysis].. [6]	2021	Syekh S A Umri, et al	Rapid Miner	Data was obtained from the Jakarta Provincial Government site (data.jakarta.go.id), including Air Pollution Standard Index (ISPU) data from Central, North, South, East, and West Jakarta. It supports environmental and health policymaking to combat pollution.
7.	Klasifikasi [Classification]…[7]	2024	Putri Nabillah, et al	Rapid Miner	Data from the Dumai City Social Service (DTKS Jan-Dec 2022) was used as the government basis for

					determining aid recipients. This study supports accurate KIS recipient classification for targeted distribution.
8.	Klasifikasi [Classification].…[8]	2024	Yua Isman Islam, Zaehol Fatah	Rapid Miner	Socio-economic indicators from East Java were used to map and address poverty. The KNN model achieved 92.11% accuracy in poverty classification.
9.	Klasifikasi [Classification].…[9]	2024	Annisa Rahma Putri, et al	Rapid Miner	Official village data from Geyongan (BLT-DD aid recipients) showed that KNN improves classification accuracy and transparency in village-level aid distribution.
10.	Implementasi [Implementation]...[10]	2020	Anwar Pauji, et al	Rapid Miner	High-poverty area data from Ciherang and Ciaro Villages (Nagreg) proved KNN effective in determining BLT recipients based on economic characteristics.
11.	Penerapan [Application]…[11]	2021	Dewi Marini Umi Atmaja, Et al	Rapid Miner	COVID-19 data from Pikobar.jabarprov.go.id was used to support mapping risk levels in West Java and guide public health policies.
12.	Penerapan [Application]…[12]	2024	Sri Widia Pebrianti, et al	Rapid Miner	Child nutrition data from Bojongemas Village Posyandu showed KNN achieved 92% accuracy in early stunting detection.
13.	Implementasi [Implementation]…[13]	2021	Ahmad Khairi, et al	Rapid Miner	Underserved household data from Sapikerep Village yielded highest KNN accuracy of 98.68% at K=5 and K=7, making aid distribution more targeted.
14.	Pengklasifikasian [Categorization]…[[14]	2024	Ibrahim, Fitrah Yuridka	Rapid Miner	Data from Antasan Besar showed 97.91% accuracy using KNN to classify underprivileged citizens and optimize aid delivery.
15.	Klasifikasi [Classification]…[15]	2024	Ryan Hamonangan, et al	Rapid Miner	Data from 1,221 residents of Ciherang and Ciaro Villages (2022–2023) analyzed with K=6 and RapidMiner achieved 81.56% classification accuracy.
16.	Penerapan [Application]…[16]	2024	Ridlwanul Fitra,	Rapid Miner	Socio-economic data from Kapuk Muara (income, dependents, housing status) showed KNN (K=8) effective in classifying aid eligibility.

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17.	Analisis [Analysis]……[17]	2023	Akrim Teguh Suseno, et al	Rapid Miner	MSME aid recipient data from Pekalongan Cooperatives Office reached 94.94% KNN accuracy for post-COVID economic recovery programs.
18.	Penerapan [Application]…[18]	2024	Elsa Pitaloka, et al	Python	Public dataset from Kaggle (1901–2018 rainfall) supports disaster mitigation and flood policy planning.
19.	Penerapan [Application]…[19]	2023	Agung Triayudi	Rapid Miner	Bansos recipient data from Ministry of Social Affairs and local social offices found K=7 most effective for classifying aid eligibility.
20.	Klasifikasi [Classification]…[20]	2024	Annisa Rahma Putri, et al	Rapid Miner	Geyongan Village data achieved 87.31% accuracy at K=9; Confusion Matrix: precision 89.06%, recall 85.07%, F1-score 87.02%.
21.	Penerapan [Application]…[21]	2021	Rizal Wahyudi, et al	PHP dan phpMyAdmin	Bluto Village Posyandu nutrition monitoring data achieved 88% accuracy at K=3, supporting national child health programs.
22.	Implementasi [Implementation]…[22]	2022	Mario Sabar	Python	Crime data from Serang Police achieved 91.8% accuracy with K=1, proving KNN suitable for classifying regional criminal data.
23.	Analisis [Analysis]……[23]	2024	Widya Bhakti Dira, Jarot Priang gono	Rapid Miner	Vehicle theft data (2018–2023) from Malang Police showed best KNN performance at K=9 with 94.21% accuracy, 94.97% recall, 93.19% precision, 93.89% F1-score.
24.	Implementasi [Implementation]…[24]	2024	Nathan Ramadhani, et al	Python	Disability aid data from DKI Jakarta Social Service used KNN for clustering aid recipients and minimizing distribution errors.
25.	Klasifikasi [Classification]…[25]	2022	Wulan Suci, et al	Rapid Miner	Sindangpano Village data (2021) on social and food aid reached 99.57% accuracy using KNN for efficient recipient targeting.
26.	Penerima [Recipients]..[26]	2021	Haidah Putri, et al	Rapid Miner	KKS recipient data (6,491 people) from Harjamukti, Cirebon was integrated with a web/mobile system for real-time aid recipient verification and selection.

One of the instance-based classification methods is K-Nearest Neighbor (KNN), an algorithm that is effective in understanding complex data patterns, making it suitable

for government data. Government data often contains patterns that can be identified based on the proximity of data points, which makes the K-Nearest Neighbor method an appropriate choice for implementation.

Examples of government data include geospatial and environmental statistics (such as flood-prone areas and air pollution identification), demographic data (such as socioeconomic classification of citizens for social assistance policies), law enforcement and security data (such as regional grouping based on crime rates), financial and economic data (such as identifying budget misuse in the distribution of social aid), and public health statistics (such as classifying areas based on health levels). Additionally, the K-Nearest Neighbor algorithm has been used in research involving community economic profiles to map social assistance recipients (such as KKS and BLT), helping ensure that funds are distributed accurately to those truly in need. Governments can use this method to identify groups that genuinely require assistance, allowing for more efficient and purposeful resource allocation.

Furthermore, data processing supports governments in better utilizing resources by ensuring budgets are spent according to prioritized needs. Studies involving age and types of driver's license applications, as well as air quality index classification, have also applied this algorithm to analyze characteristics and categorize datasets. Policy-making becomes more effective when it is based on data-driven analysis. The results of data processing serve as factual references that can be used as reliable recommendations.

Errors in manual data processing can also be minimized through the use of data mining implementation with the K-Nearest Neighbor (KNN) algorithm. Decisions become more targeted and are based on facts, with data serving as a primary support in the decision-making process. In the aforementioned cases, it can be concluded that the selection of beneficiaries, prioritization of zones, and classification of crime data can all be structured in a way that supports accountable and well-informed decisions. For example, identifying areas with high crime rates allows the government to implement strategic policies to improve security and tighten surveillance systems in those regions. Such measures can increase public trust in the government and lead to improved quality of public services.

In other research, air pollution data has been used to predict future environmental impacts and determine strategic follow-up actions for pollution control. During pandemics and disasters, data processing insights can accelerate government responses in providing aid or conducting mitigation efforts. In terms of geospatial benefits, the government can also map flood-prone areas to implement preventive measures. Decisions, therefore, become more targeted, fact-based, effective, transparent, and responsive to the needs of the community.

Based on the literature review, the most commonly used tool for classifying government data using the K-Nearest Neighbor algorithm is RapidMiner. RapidMiner is well-suited for implementing K-Nearest Neighbor due to its capability to handle large and complex datasets. Additionally, the platform supports integration with other data sources, such as SQL, Excel, and cloud services, allowing users to access data from various systems used by government agencies. RapidMiner can also present analysis results in the form of graphs and charts, making data interpretation easier to review.

From previous studies, it can be concluded that the success of K-Nearest Neighbor implementation is influenced by the optimal number of neighbors (k). Other studies have also utilized real-time data to test their models, encouraging more timely and responsive policy actions that reflect changes in real-world conditions.

Therefore, it can be concluded that the use of the KNN algorithm is quite effective in supporting government decision-making across various sectors, such as social welfare, health, education, and public safety. As the volume and complexity of data continue to grow, the use of the KNN algorithm is expected to be a suitable solution for public policy development and as a foundation for more accurate, efficient, and data-driven decision-making.

4. CONCLUSION

Based on the results of the literature review, this study highlights the application of the K-Nearest Neighbor (KNN) algorithm in data classification to support government policy-making. In the increasingly advanced digital era, data processing has become a significant factor in optimizing policies, especially with the growing volume of data generated across various government sectors. The literature findings indicate that KNN has been applied in numerous areas of government policy, including welfare recipient classification, healthcare planning, crime pattern analysis, environmental planning, and population planning. Overall, this systematic literature review demonstrates that the use of KNN in government data classification has a positive impact on shaping follow-up policies, enabling the government to make more targeted decisions and enhancing transparency in governance. The KNN algorithm used in this study has been successfully applied in the classification of social assistance recipients, public health planning, crime mapping, environmental management, and population management. The government can integrate the results of this analysis into a decision support system, enabling policies to be more accurate and fact-based.

5. SUGGESTED

Based on the results of this study, the application of the K-Nearest Neighbor (KNN) algorithm is recommended as a classification method to support government policy decision-making, especially in sectors such as social assistance, public health, environmental monitoring, and law enforcement. Future researchers are encouraged to expand the literature review by integrating comparative analysis with other classification algorithms such as Decision Tree or Random Forest to enrich the findings and identify the most effective models. In addition, it is suggested to apply the KNN method on real-time datasets or develop a prototype decision support system (DSS) that incorporates KNN-based classification to evaluate its practical implementation in public service institutions. Enhancing the diversity of case studies and data characteristics will provide broader insight into the adaptability of KNN in various government policy contexts.

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