Implementation Of The K-Nearest Neighbor Method For An Equipment Inventory System At The XYZ City Fire And Disaster Management Department

Dafa Arya Wijaya, Manajemen Informatika, Politeknik Negeri Sriwijaya, dafaarya@gmail.com[1]
Febie Elfaladonna, Manajemen Informatika, Politeknik Negeri Sriwijaya,febie.elfakhrul@gmail.com[2]*
Meivi Kusnandar, Manajemen Informatika, Politeknik Negeri Sriwijaya,meivi_kusnandar_mi@polsri.ac.id[3]
Deri Darfin, Manajemen Informatika, Politeknik Negeri Sriwijaya,deri_darfin_mi@polsri.ac.id[4]
Devi Sartika, Manajemen Informatika, Politeknik Negeri Sriwijaya, devi_sartika_mi@polsri.ac.id[5]
*Corresponding Author**: febie.elfakhrul@gmail.com

Abstract

Background : Inventory management is essential for ensuring the availability, traceability, and proper maintenance of organizational assets. However, the XYZ City Fire and Disaster Management Department still manages inventory using Microsoft Excel, resulting in inefficient data processing, limited accessibility, and a high risk of data entry errors.

Purpose : This study aims to develop a web-based inventory management system integrated with the K-Nearest Neighbor (KNN) algorithm to improve inventory management efficiency and automatically evaluate equipment feasibility.

Methodology : A web-based inventory application was developed to manage inventory records and classify equipment conditions using the K-Nearest Neighbor (KNN) method. System performance was evaluated using classification metrics, including accuracy, precision, recall, and F1-score.

Findings : The developed system successfully automated inventory management and equipment feasibility assessment. Experimental results showed that the KNN model achieved 100% accuracy, precision, recall, and F1-score, demonstrating its effectiveness in classifying equipment as either suitable for continued use or requiring replacement.

Implications : The proposed system provides a practical solution for improving inventory management by increasing data accuracy, accelerating decision-making, and supporting real-time monitoring of equipment conditions. Although the system performed exceptionally well in this study, further validation using larger and more diverse datasets is recommended to evaluate its scalability and generalizability..

Originality : This study integrates a web-based inventory management system with the K-Nearest Neighbor algorithm to automate equipment feasibility evaluation in a fire and disaster management agency, providing an accurate, efficient, and real-time decision-support tool for inventory management.

Keywords *: inventory, k-nearest neighbor, classification, web-based application, fire department*

INTRODUCTION

The rapid development of information technology has significantly transformed business processes and public services, including inventory management systems in government institutions. According to the 2021 National Socio-Economic Survey (Susenas), approximately 62.10% of Indonesia's population had internet access, while 90.54% of households owned and used mobile phones (Saputra, 2024). These figures indicate that digital technologies have become an integral part of

organizational operations, enabling more efficient data management, information accessibility, and decision-making. Consequently, many public institutions have shifted from manual record-keeping to digital information systems to improve operational efficiency and data accuracy.

Inventory management is a systematic process of recording, monitoring, and controlling organizational assets to ensure their availability, traceability, and operational readiness (Hidayat, 2021). In many institutions, inventory records are still maintained manually using spreadsheet applications, which often result in data duplication, input errors, delayed updates, and difficulties in tracking equipment conditions. These limitations reduce administrative efficiency and may adversely affect organizational performance, particularly in emergency service agencies where equipment availability and reliability are critical.

One institution facing these challenges is the XYZ City Fire and Disaster Management Department (DPKPB), which is responsible for emergency response to fires and disasters. Since establishing nine fire stations across the city in 2023, the department has managed a wide range of operational equipment, including fire engines, personal protective equipment, communication devices, and fire extinguishers. Based on interviews conducted on 14 March 2025 with the personnel administration officer, the inventory process is still performed using Microsoft Excel. Equipment information, including item names, quantities, storage locations, and physical conditions, is recorded manually and updated periodically. Although this approach is simple to implement, it lacks automation, provides limited accessibility, and requires separate physical inspections to evaluate equipment condition, making inventory management inefficient and time-consuming.

Recent studies have demonstrated the effectiveness of machine learning techniques for asset classification and decision support. Mulya et al. (2024) emphasized that equipment feasibility assessment plays an important role in organizational asset management by considering variables such as purchase year, service life, damage level, usage intensity, and physical condition. Similarly, Nijunnihayah et al. (2024) reported that the K-Nearest Neighbor (KNN) algorithm achieved approximately 95% classification accuracy in predicting equipment feasibility, highlighting its capability as a reliable classification method. The KNN algorithm determines the class of a new instance by measuring its similarity to neighboring training data using distance-based calculations, commonly the Euclidean distance (Yunus & Pratiwi, 2023). Because of its simplicity, high classification performance, and ease of implementation, KNN has become one of the most widely adopted supervised learning algorithms for decision-support applications (Said et al., 2022).

Despite these advances, previous studies have primarily focused on evaluating classification algorithms or predicting equipment feasibility independently. Limited attention has been given to integrating machine learning-based feasibility assessment into a web-based inventory management system capable of supporting real-time inventory recording, equipment monitoring, and automated decision-making within emergency response organizations. As a result, inventory management and equipment condition assessment are often conducted separately, reducing operational efficiency and delaying maintenance or replacement decisions.

This study addresses this gap by developing a web-based inventory management system integrated with the K-Nearest Neighbor algorithm to automate equipment feasibility evaluation in the XYZ City Fire and Disaster Management Department. The proposed system combines digital inventory management with intelligent classification, enabling real-time equipment monitoring while automatically recommending whether equipment remains serviceable or requires replacement. By integrating inventory management and equipment feasibility assessment into a single platform, the proposed approach is expected to improve data accuracy, accelerate decision-making, enhance operational efficiency, and support the preparedness of emergency response equipment. The novelty of

Corresponding Authors : febie.elfakhrul@gmail.com

this research lies in the implementation of an integrated web-based inventory information system that incorporates KNN-based equipment feasibility classification to provide automated decision support for inventory management in a fire and disaster management agency.

LITELATUR REVIEW

2.1. Inventory Management

Inventory management is the systematic process of recording, monitoring, and controlling organizational assets to ensure their availability, traceability, and efficient utilization. Effective inventory management enables organizations to maintain accurate information regarding the quantity, type, condition, acquisition date, specifications, and value of assets, thereby supporting operational planning and decision-making (Usnaini et al., 2021). In public service organizations, particularly emergency response agencies, an efficient inventory management system is essential to ensure that operational equipment remains available and ready for deployment whenever required.

2.2. K-Nearest Neighbor (KNN)

The K-Nearest Neighbor (KNN) algorithm is a supervised machine learning method widely used for classification tasks because of its simplicity and effectiveness. The algorithm classifies a new observation based on the majority class among its K nearest neighbors in the training dataset (Argina, 2020). Similarity between observations is commonly measured using the Euclidean distance, which is expressed as

$$euc = \sqrt{(\sum_{i=1}^{n} (pi - qi)^2)} \quad (1)$$

where (pi) represents the value of the *i*-th attribute in the training data, (qi) represents the corresponding attribute in the testing data, and (n) denotes the total number of attributes. After calculating the distances, the algorithm ranks the neighboring observations, selects the K closest samples, and assigns the class that appears most frequently among these neighbors (Barokah & Kurniawan, 2020). Owing to its ability to classify objects based on similarity, KNN has been widely applied in decision-support systems and equipment feasibility assessment.

2.3. System Analysis

System analysis is the process of evaluating an existing system to identify its strengths, weaknesses, and functional requirements before developing an improved system. The objective is to understand current business processes, identify operational problems, and define the functional and non-functional requirements of the proposed system. This process typically involves observations, interviews, documentation analysis, and the development of system models, such as flowcharts and data flow diagrams, to support the design and implementation of an effective information system (Muhidin & Davitra, 2020).

2.4. Web-Based Inventory System

A web-based inventory system is an information system designed to record, monitor, and manage organizational assets through an online platform that can be accessed in real time. Such systems improve inventory accuracy by centralizing data management, minimizing manual recording errors, and facilitating rapid retrieval of inventory information. In emergency service organizations, including fire and disaster management agencies, a web-based inventory system enables personnel to monitor

Corresponding Authors : febie.elfakhrul@gmail.com

equipment availability and condition efficiently, thereby supporting timely maintenance and operational readiness (Yaku Danga et al., 2023). When integrated with machine learning techniques such as KNN, the system can further automate equipment feasibility evaluation and provide decision support for equipment maintenance and replacement.

METHODOLOGY

The research procedure is illustrated in **Figure 1** and consists of five main stages: observation, problem identification, data collection, data preprocessing, and system development.

Observation. The study began with direct observation at the XYZ City Fire and Disaster Management Department to understand the existing inventory management process and identify operational problems. Interviews with relevant personnel were conducted to obtain information regarding current inventory practices and system requirements (Zanariyah, 2024).

Problem Identification. Based on the observation results, three major problems were identified. First, inventory management was still performed using Microsoft Excel, resulting in inefficient data management and increasing the risk of data entry errors and duplication. Second, the department did not have an integrated web-based inventory management system. Third, no automated mechanism was available to evaluate equipment feasibility, causing maintenance and replacement decisions to rely solely on manual inspection.

Data Collection. Data were collected through interviews with department personnel, direct observation of inventory activities, and a literature review of books, scientific journals, and other relevant publications related to inventory management and the K-Nearest Neighbor algorithm.

Data Preprocessing. Before implementing the classification model, the collected inventory data underwent preprocessing to improve data quality. This stage included data cleaning, duplicate removal, missing value handling, normalization, and categorical data transformation into numerical attributes suitable for K-Nearest Neighbor computation. Data preprocessing was performed using the **Orange** data mining platform. After preprocessing, the dataset contained no missing values, duplicate records, or outliers, ensuring its suitability for model development (Sartika et al., 2025).

The preprocessed dataset was subsequently used to develop and evaluate the web-based inventory management system integrated with the K-Nearest Neighbor algorithm for equipment feasibility classification.

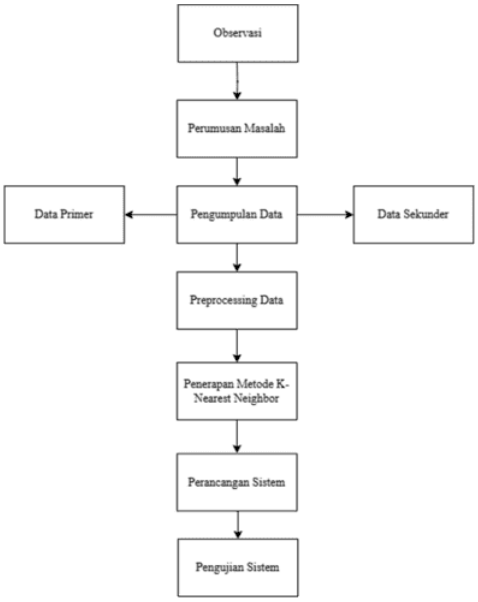


Figure 1 Research Design

Corresponding Authors : febie.elfakhrul@gmail.com

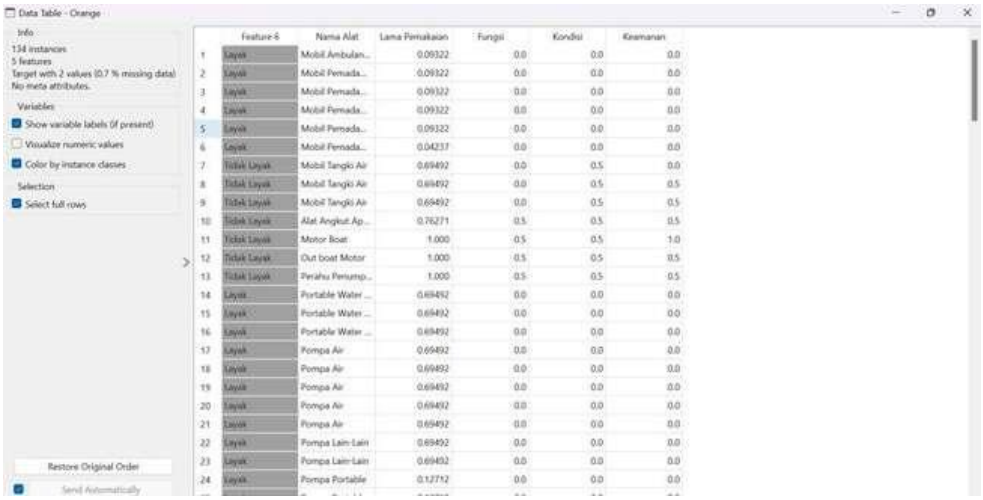


Figure 2. Step by step Preprocessing with Tools Orange

No	Nama	Lama Pemakaian	Fungsi	Kondisi	Keamanan	Status
1	Mobil Ambulance	13	2	2	1	Layak
2	Mobil Pemadam Kebakaran	7	2	2	1	Layak
3	Mobil Pemadam Kebakaran	7	2	2	1	Layak
4	Mobil Pemadam Kebakaran	7	2	2	1	Layak
5	Mobil Pemadam Kebakaran	7	2	2	1	Layak
6	Mobil Pemadam Kebakaran	7	2	2	1	Layak
7	Mobil Tangki Air	84	2	3		Tidak layak
8	Mobil Tangki Air	84	2		2	Tidak layak
9	Mobil Tangki Air	84	2	3		Tidak layak
10	Alat Angkut Apung Bermotor Barang Lain-Lain	92	3	3	2	Tidak layak
11	Motor Boat	120		3	3	Tidak layak
12	Out boat Motor	120	3	3	2	Tidak layak
13	Perahu Penumpang	120	3	3	2	Tidak layak
14	Portable Water Pump	84	2	2	1	Layak
15	Portable Water Pump	84	2	2	1	Layak
16	Portable Water Pump	84	2	2	1	Layak
17	Pompa Air	84	2	2	1	Layak
18	Pompa Air	84	2	2	1	Layak
19	Pompa Air	84	2	2	1	Layak
20	Pompa Air	84	2	2	1	Layak
21	Pompa Air	84	2	2	1	Layak
22	Pompa Lain-Lain	84	2	2	1	Layak
23	Pompa Lain-Lain	84	2	2	1	Layak

Figure 3. Dataset Through in Processing

K-Nearest Neighbor (KNN) Implementation. The K-Nearest Neighbor (KNN) algorithm was employed to classify the feasibility of firefighting equipment based on historical inventory data. Equipment feasibility was evaluated using four assessment criteria: **service life, functional performance, overall physical condition, and safety**, as presented in **Table 1**. Each criterion was represented by categorical attributes that were converted into numerical values during the preprocessing stage to facilitate distance calculation.

For the **service life** criterion, equipment was categorized into three groups according to the duration of use, namely **1–30 months (Very Good), 31–60 months (Good), and 61–90 months (Poor)**. The remaining criteria—**functional performance, physical condition, and safety**—were assigned

Corresponding Authors : febie.elfakhrul@gmail.com

numerical weights based on their qualitative assessment levels, as summarized in **Tables 2–5**. These numerical representations enabled the calculation of similarity between training and testing instances. The KNN model requires the determination of the parameter **K**, which specifies the number of nearest neighbors considered during the classification process. In this study, the value of **K = 5** was selected empirically to achieve a balance between classification stability and sensitivity to noise. A relatively small value of K may produce unstable predictions due to outliers, whereas a larger value may reduce classification accuracy by incorporating observations from different classes. Therefore, **K = 5** was considered appropriate for the characteristics of the dataset used in this study.

The similarity between testing data and training data was calculated using the **Euclidean Distance** metric, as expressed in Equation (2). After calculating the distances, the five nearest neighbors were identified, and the equipment feasibility was determined using a majority voting mechanism. The final classification categorized each equipment item as either **feasible for continued use** or **requiring replacement**, providing decision support for inventory management within the XYZ City Fire and Disaster Management Department.

Table 1. Data Criteria

No	Nama Kriteria
1	Lama Pemakaian
2	Pengujian Fungsi
3	Kondisi Keseluruhan
4	Keamanan

Table 2. Criteria Long Ago Use

No	Nama sub kriteria	Keterangan
1	1-30 Bulan	Sangat Baik
2	31-60 Bulan	Baik
3	61-90 Bulan	Buruk

Table 3. Weight Criteria for Function

Nama sub kriteria	Bobot
Sangat Baik	1
Baik	2
Kurang Baik	3
Tidak Baik	4

Table 4. Weight Criteria for Condition

Nama Sub Kriteria	Bobot
Sangat Bagus	1
Bagus	2
Kurang Bagus	3
Tidak Bagus	4

Table 5. Weight Criteria for Savety

Nama sub kriteria	Bobot
Aman	1
Tidak aman	2

Corresponding Authors : febie.elfakhrul@gmail.com

The next stage involved determining the value of the **K** parameter, which represents the number of nearest neighbors considered during the classification process. The selection of an appropriate K value is important because it directly affects the classification performance. A very small K value may lead to predictions that are highly sensitive to noise and outliers, whereas an excessively large K value may include observations from different classes, thereby reducing classification accuracy. In this study, **K = 5** was selected empirically as it provides a balance between robustness and classification accuracy while minimizing the influence of outliers in the dataset.

After determining the K value, the similarity between the training and testing data was calculated using the **Euclidean Distance** metric, as presented in Equation (2). The calculated distances were then ranked in ascending order, and the five nearest neighbors were identified. The class label of the testing instance was determined using a majority voting mechanism among these nearest neighbors.

The training dataset consisted of historical inventory records whose equipment feasibility status had been previously determined. These labeled records served as the reference data for the KNN classification model. A sample of the training dataset is presented in **Figure 4**.

No	Nama	Lama Pemakaian	Fungsi	Kondisi	Keamanan	Status
1	Mobil Pemadam Kebakaran	7	2	2	1	Layak
2	Mobil Ambulance	13	2	2	1	Layak
3	Pompa Portable	17	2	2	1	Layak
4	Fire Hose 1,5 inch	84	4	4	2	Tidak Layak
5	Fire Hose 2,5 inch	84	4	4	2	Tidak Layak
6	Tabung Pemadam Kebakaran (APAR)	31	2	2	1	Layak
7	Portable Fire Pump	84	2	2	1	Layak
8	Handy Talkie	38	2	2	1	Layak
9	Alat komunikasi radio SSB Lain	2	2	2	1	Layak
10	Lampu Senter	2	2	2	1	Layak

Figure 4. Sample of the training dataset.

The testing dataset contained new equipment records that had not yet been classified. Each testing instance was compared with all training instances to calculate the Euclidean distance and identify its five nearest neighbors. Based on the majority class among these neighbors, the system classified each equipment item as either **feasible for continued use** or **requiring replacement**. A sample of the testing dataset is shown in **Figure 5**.

No	Nama	Lama Pemakaian	Fungsi	Kondisi	Keamanan	Status
1	Breathing aparatus	96	4	3	2	?

Figure 5. Sample of the testing dataset.

The detailed classification process between the training and testing datasets is presented in the following section.

1. Distance Car Fire Departement

$$d(xi,yi) = \sqrt{\sum_{i=1}^{n} (xi - yi)^2}$$

$$= \sqrt{(7-96)^2 + (2-4)^2 + (2-3)^2 + (1-2)^2}$$

$$= 89.05054744$$

2. Distance Car Ambulance

Corresponding Authors : febie.elfakhrul@gmail.com

$$d(xi,yi) = \sqrt{\sum_{i=1}^{n} (xi - yi)^2}$$

$$= \sqrt{(13-96)^2 + (2-4)^2 + (2-3)^2 + (1-2)^2}$$

$$= 83.05419917$$

3. Distance Pump Portable

$$d(xi,yi) = \sqrt{\sum_{i=1}^{n} (xi - yi)^2}$$

$$= \sqrt{(17-96)^2 + (2-4)^2 + (2-3)^2 + (1-2)^2}$$

$$= 79.0569415$$

4. Distance Fire Hose 1,5 Inch

$$d(xi,yi) = \sqrt{\sum_{i=1}^{n} (xi - yi)^2}$$

$$= \sqrt{(84-96)^2 + (4-4)^2 + (4-3)^2 + (2-2)^2}$$

$$= 84.21401309$$

5. Distance Fire Hose 2,5 inch

$$d(xi,yi) = \sqrt{\sum_{i=1}^{n} (xi - yi)^2}$$

$$= \sqrt{(84-96)^2 + (4-4)^2 + (4-3)^2 + (2-2)^2}$$

$$= 84.21401309$$

6. Distance Tube Fire attendence (APAR)

$$d(xi,yi) = \sqrt{\sum_{i=1}^{n} (xi - yi)^2}$$

$$= \sqrt{(31-96)^2 + (2-4)^2 + (2-3)^2 + (1-2)^2}$$

$$= 31.144823$$

7. Portable Fire Pump

$$d(xi,yi) = \sqrt{\sum_{i=1}^{n} (xi - yi)^2}$$

$$= \sqrt{(84-96)^2 + (2-4)^2 + (2-3)^2 + (1-2)^2}$$

$$= 12.36931688$$

8. Handy Talkie

$$d(xi,yi) = \sqrt{\sum_{i=1}^{n} (xi - yi)^2}$$

$$= \sqrt{(38-96)^2 + (2-4)^2 + (2-3)^2 + (1-2)^2}$$

$$= 58.07753438$$

9. Tools communication radionSSB and other

$$d(xi,yi) = \sqrt{\sum_{i=1}^{n} (xi - yi)^2}$$

$$= \sqrt{(2-96)^2 + (1-4)^2 + (1-3)^2 + (1-2)^2}$$

$$= 94.04786016$$

10. Lamp Senter

$$d(xi,yi) = \sqrt{\sum_{i=1}^{n} (xi - yi)^2}$$

$$= \sqrt{(2-96)^2 + (1-4)^2 + (1-3)^2 + (1-2)^2}$$

$$= 94.04786016$$

Berikut ini merupakan hasil perhitungan *Euclidian Distance* Breathing Aparatus

Table 6. Result Calculation Euclidian Distance Breathing Aparatus

No	Nama	Lama pemakaian	Fungsi	Kondisi	Keamanan	Jarak	Status

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1	Mobil Pemadam Kebakaran	39	2	2	1	57.05261	Layak
2	Mobil Ambulance	13	2	2	1	83.05419	Layak
3	Pompa Portable	17	2	2	1	79.05694	Layak
4	Fire Hose 1,5 inch	84	4	4	2	12	Tidak Layak
5	Fire Hose 2,5 inch	84	4	4	2	12	Tidak Layak
6	Tabung Pemadam (APAR)	31	2	2	1	65.06919	Layak
7	Portable Fire Pump	84	2	2	1	12.36931	Layak
8	Handy Talkie	38	2	2	1	38.11824	Layak
9	Alat Komunikasi Radio SSB Lain	2	1	1	1	94.04786	Layak
10	Lampu Senter	2	2	2	1	94.04786	Layak

Table 7. Result Calculation Training data Euclidian Distance Breathing Aparatus

No	Nama	Lama	Fungsi	Kondisi	Keamanan	Jarak	Ranking	Status
1	Mobil Pemadam Kebakaran	39	2	2	1	89.05054	83	Layak
2	Mobil Ambulance	13	2	2	1	83.05419	82	Layak
3	Pompa Portable	17	2	2	1	79.05694	67	Layak
4	Fire Hose 1,5 inch	84	4	4	2	12	2	Tidak Layak

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5	Fire Hose 2,5 inch	84	4	4	2	12	2	Tidak Layak
6	Tabung Pemadam Kebakaran (APAR)	31	2	2	1	65.06 919	51	Layak
7	Portable Fire Pump	84	2	2	1	12.36 931	15	Layak
8	Handy Talkie	38	2	2	1	38.11 824	45	Layak
9	Alat Komunika su Radio SSB Lain	2	1	1	1	94.04 786	88	Layak
10	Lampu Senter	2	2	2	1	94.04 786	88	Layak

Next, the system selects the five nearest data points as neighbors (k=5), then determines the class of the test data based on the majority class of those neighbors..

Table 8. Values K=5

No	Nama	Lama Pemakaian	Fungsi	Kondisi	Keamanan	Jarak	Status
1	Alat Angkut Apung Bermotor Lain-Lain	92	3	3	2	4.242640 687	Tidak layak
2	Fire Hose 1,5 inch	84	4	4	2	12	Tidak Layak
3	Fire Hose 2,5 inch	84	4	4	2	12	Tidak Layak
4	Mobil Tangki Air	84	2	3	2	12.20655 562	Tidak Layak
5	Portbale Fire Pump	84	2	2	1	12.36931 688	Layak

Corresponding Authors : febie.elfakhrul@gmail.com

The classification results presented in **Table 3** indicate that four neighboring training instances were classified as **not feasible**, leading the KNN algorithm to classify the testing instance of the **Breathing Apparatus** as **not feasible**. In the KNN algorithm, the Euclidean distance determines the similarity between testing and training data. Smaller distance values indicate higher similarity, whereas larger distances represent lower similarity. Consequently, the final classification is determined by the majority class among the selected nearest neighbors. To validate the manual calculation, the same dataset was evaluated using the **Orange** data mining platform. The resulting **confusion matrix** is presented in **Figure 6**.

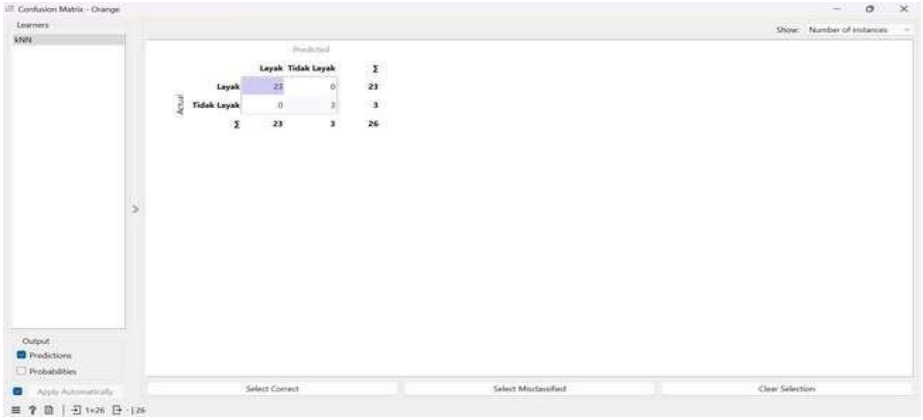


Figure 6. Confusion Matrix.

The comparison between the manual KNN calculation and the Orange implementation produced identical classification results. Using **K = 5**, both approaches classified the testing instance of the **Breathing Apparatus** as **not feasible**, confirming the correctness and consistency of the implemented classification algorithm.

3.2 System Design

The proposed inventory management system was designed using **Unified Modeling Language (UML)** to describe its functional and structural architecture. UML diagrams were developed using **Draw.io**, including the **Use Case Diagram, Class Diagram, Activity Diagram, and Sequence Diagram**, to represent user interactions, system structure, process flow, and object communication, respectively (Narulita et al., 2024). The **Use Case Diagram** illustrates the interactions between users and the system, identifying the primary functionalities provided by the application (**Figure 7**).

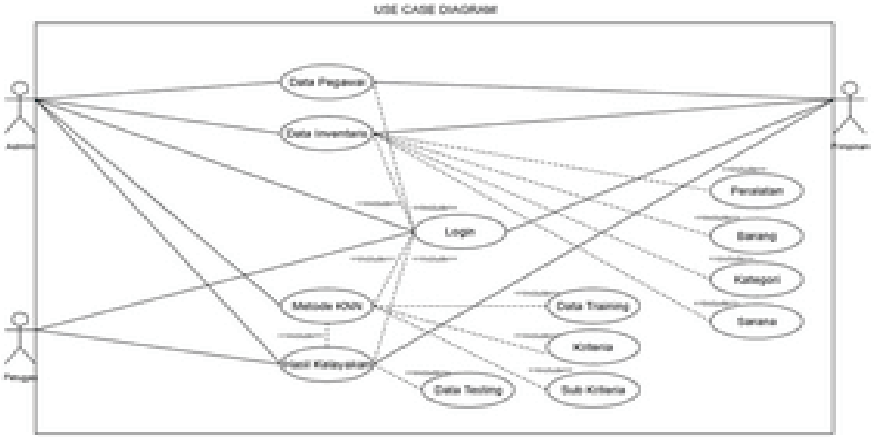


Figure 7. Use Case Diagram.

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The **Class Diagram** describes the structural relationships among system classes, including their attributes, methods, and associations, thereby representing the overall architecture of the application (**Figure 8**).

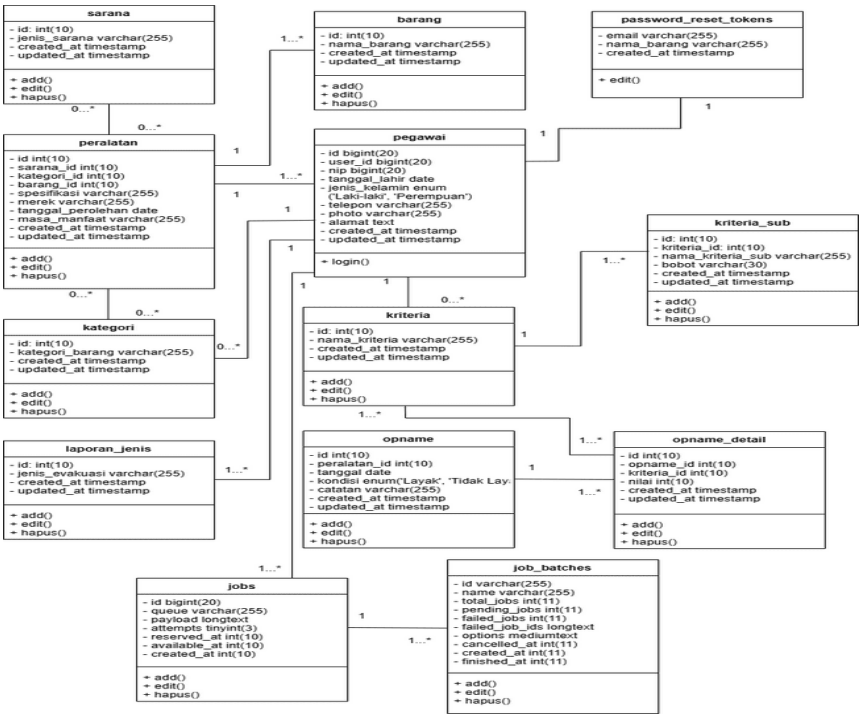


Figure 8. Class Diagram.

The **Activity Diagram** models the workflow of inventory management and equipment feasibility assessment from the initiation of a process to its completion (**Figure 9**).

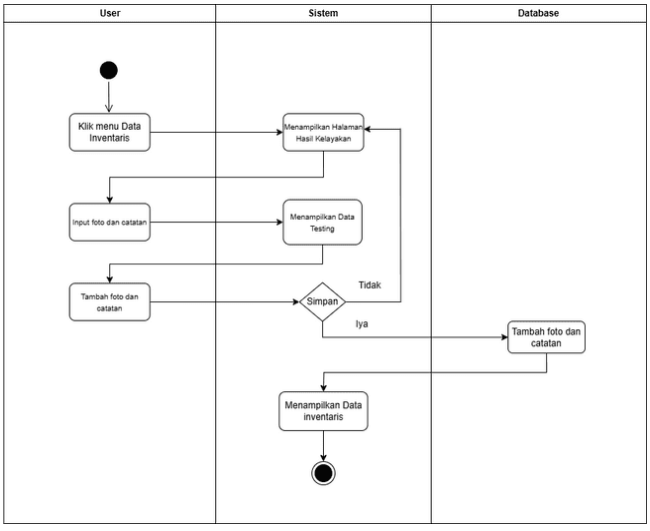


Figure 9. Activity Diagram.

The **Sequence Diagram** illustrates the chronological interactions among system objects during the execution of inventory management and equipment classification processes (**Figure 10**).

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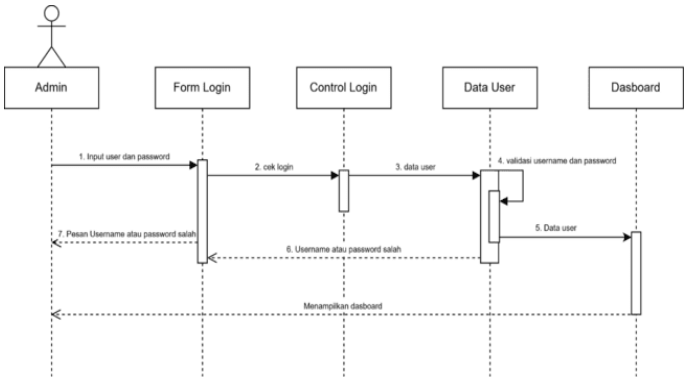


Figure 10. Sequence Diagram.

3.3 System Testing

System testing was conducted to verify that all functionalities of the proposed web-based inventory management system operated correctly and satisfied the specified functional requirements. Before deployment at the **XYZ City Fire and Disaster Management Department**, the application was evaluated using **Black Box Testing**, which focuses on validating system functionality by examining input-output behavior without considering the internal program structure. The testing confirmed that all major features, including inventory management, equipment feasibility classification, data processing, and report generation, performed as expected.

RESULT AND DISCUSSION

4.1 System Implementation

The proposed web-based inventory management system was successfully implemented by integrating the **K-Nearest Neighbor (KNN)** algorithm into the equipment feasibility assessment module. The system interface is shown in **Figure 9**.

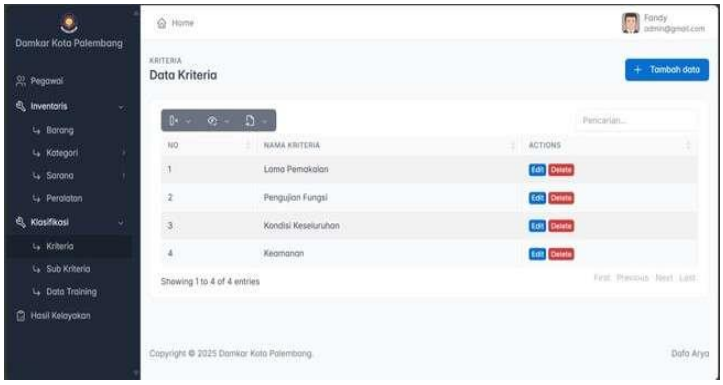


Figure 9. Web-based inventory management system with KNN implementation.

The implemented system automatically classifies equipment feasibility based on four evaluation criteria: service life, functional performance, physical condition, and safety. For each testing instance, the KNN algorithm calculates the Euclidean distance to all training instances, identifies the five nearest neighbors (K = 5), and determines the final classification through a majority voting mechanism. Consequently, each equipment item is automatically categorized as either feasible for continued use or requiring replacement, providing objective decision support for inventory management.

The implementation demonstrated that equipment with a service life of less than 30 months and favorable functional, physical, and safety conditions was generally classified as feasible. In contrast, equipment that had been used for more than 60 months and exhibited poor functional or physical

Corresponding Authors : febie.elfakhrul@gmail.com

conditions was predominantly classified as not feasible. These results indicate that the proposed classification model effectively captures the relationship between equipment characteristics and feasibility status, thereby reducing subjectivity in maintenance and replacement decisions.

The web application provides role-based access for administrators, field officers, and managers. Administrators are responsible for managing inventory records, training datasets, testing datasets, and classification results. Field officers can perform equipment inspections and obtain automated feasibility assessments, while managers are provided with real-time reports to support maintenance planning and strategic decision-making. By integrating inventory management with intelligent equipment classification, the proposed system improves data consistency, reduces manual processing time, and enhances decision-making efficiency.

4.2 System Testing

Functional testing was conducted using the **Black Box Testing** approach to verify that every feature of the application operated according to its specified requirements. The testing covered all major modules, including user authentication, inventory management, training data management, testing data management, equipment feasibility classification, profile management, and dashboard access for different user roles.

The testing results demonstrated that all functional requirements were successfully fulfilled. User authentication correctly validated both valid and invalid login credentials. Inventory management functions including data creation, modification, deletion, and retrieval operated as expected. Similarly, the training and testing data modules successfully supported data management and KNN-based equipment classification. The equipment feasibility module accurately displayed classification results generated by the KNN algorithm, while dashboard and reporting functions were accessible according to user authorization levels.

Overall, the Black Box Testing results confirmed that all tested functionalities achieved a **100% success rate**, indicating that the developed application met its functional requirements and was ready for practical implementation within the XYZ City Fire and Disaster Management Department.

Table 9. Testing Result

No.	Function Tested	Test Procedure	Expected Result	Test Result
Public Page				
1	Login Page	Verify valid username and password	The system successfully logs in and displays the dashboard with menus according to the user's role.	**Passed**
		Verify invalid username or password	Login fails and the system redirects the user back to the login page.	**Passed**
Administrator Page				
2	Dashboard	Access the dashboard after logging in as an administrator	The dashboard displays all available application menus.	**Passed**
3	Inventory Menu	Open the Inventory menu	The inventory list is displayed successfully.	**Passed**
		Select one of the inventory categories	The selected inventory category (items, equipment, categories, or facilities) is displayed correctly.	**Passed**

Corresponding Authors : febie.elfakhrul@gmail.com

No.	Function Tested	Test Procedure	Expected Result	Test Result
		Add new inventory data	The system displays the inventory data entry form.	**Passed**
		Edit inventory data	The system displays the inventory editing form.	**Passed**
		Delete inventory data	A confirmation message ("Are you sure you want to delete this data?") is displayed.	**Passed**
4	Training Data Menu	Open the Training Data menu	The training dataset is displayed successfully.	**Passed**
		Add training data	The system displays the training data entry form.	**Passed**
		Edit training data	The system displays the training data editing form.	**Passed**
		Delete training data	A confirmation message is displayed before deleting the selected data.	**Passed**
5	Equipment Feasibility Menu	Open the Equipment Feasibility menu	The equipment feasibility pop-up window is displayed.	**Passed**
		View equipment feasibility data	Equipment feasibility information, including service life, functionality, condition, and safety, is displayed correctly.	**Passed**
		Add testing data	The system displays the testing data entry form.	**Passed**
		Edit feasibility data	The system displays the feasibility data editing form.	**Passed**
		Delete feasibility data	A confirmation message is displayed before deleting the selected data.	**Passed**
6	Profile Menu	Open the Profile menu	User profile information is displayed correctly.	**Passed**
		Add user data	The system displays the user data entry form.	**Passed**
		Edit user data	The system displays the user data editing form.	**Passed**
		Delete user data	A confirmation message is displayed before deleting the selected user data.	**Passed**
Field Officer Page				
7	Dashboard	Access the dashboard after logging in as a field officer	The dashboard displays all menus available for the field officer role.	**Passed**
8	Equipment Feasibility	Open the Equipment Feasibility menu	The K-Nearest Neighbor classification results are displayed successfully.	**Passed**
Manager Page				

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No.	Function Tested	Test Procedure	Expected Result	Test Result
9	Dashboard	Access the dashboard after logging in as a manager	The dashboard displays all menus available for the manager role.	**Passed**
10	Inventory Menu	Open the Inventory menu	The inventory list is displayed successfully.	**Passed**
		Select one of the inventory categories	The selected inventory category (items, equipment, categories, or facilities) is displayed correctly.	**Passed**
11	Equipment Feasibility	Open the Equipment Feasibility menu	The K-Nearest Neighbor classification results are displayed successfully.	**Passed**

CONCLUSION

This study successfully developed a web-based inventory management system integrated with the K-Nearest Neighbor (KNN) algorithm to support equipment feasibility assessment at the XYZ City Fire and Disaster Management Department. The proposed system improves inventory management by providing a faster, more structured, and data-driven approach to recording, monitoring, and evaluating equipment conditions.

The KNN algorithm effectively classified equipment feasibility based on four evaluation criteria: service life, functionality, physical condition, and safety. Using Euclidean Distance with K = 5, the system determined equipment feasibility according to the majority class of the five nearest neighbors. Experimental results demonstrated excellent classification performance, achieving 100% accuracy, precision, recall, and F1-score. Equipment with a service life of less than 30 months and good operational conditions was consistently classified as feasible, whereas equipment with extended service life and poor conditions was classified as not feasible.

The integration of intelligent classification with a web-based inventory platform provides practical decision support for equipment maintenance and replacement planning. The proposed system enables inventory managers to monitor equipment readiness more efficiently, reduces dependence on manual assessment, and supports evidence-based decision-making to ensure operational preparedness. Future studies are recommended to evaluate the proposed approach using larger and more diverse datasets, compare KNN with other machine learning algorithms, and investigate additional equipment attributes that may further improve classification performance.

AUTHOR'S CONTRIBUTION

Dafa Arya Wijaya was responsible for the study conception, system development, data acquisition, implementation of the K-Nearest Neighbor algorithm, experimental testing, data analysis, and preparation of the original manuscript. Febie Elfaladonna supervised the research, contributed to the research design and methodology, interpreted the findings, and critically revised the manuscript. Meivi Kusnandar contributed to system validation, result evaluation, and manuscript editing. Deri Darfin contributed to software evaluation, discussion of the findings, and final manuscript review. All authors reviewed and approved the final version of the manuscript.

ACKNOWLEDGEMENTS

The authors sincerely thank the XYZ City Fire and Disaster Management Department for providing access to research data, facilities, and technical support throughout this study. The authors also

Corresponding Authors : febie.elfakhrul@gmail.com

appreciate the valuable cooperation of all staff members who assisted during the data collection and system implementation processes.

DECLARATION OF COMPETING INTEREST

The authors declare that there are no financial, professional, or personal conflicts of interest that could have influenced the research presented in this manuscript.

FUNDING

This research was conducted without financial support from any public, commercial, or not-for-profit funding agency.

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Corresponding Authors : febie.elfakhrul@gmail.com