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IMAGE MATCHING BASED HAZARDOUS MATERIAL DETECTION AND WARNING SYSTEM*

GÖRÜNTÜ EŞLEŞTİRME TABANLI TEHLİKELİ MADDE TESPİT VE UYARI SİSTEMİ

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Abstract

Transportation of dangerous goods involves many critical situations that require safety and special precautions. In accordance with the regulations, hazardous materials, which include international standards, should be closely monitored and precautions should be taken in advance according to the situation. Artificial intelligence, image processing and data analysis techniques can be used to recognize and classify the labels of dangerous goods. This is important for early action in case of an emergency. If hazardous materials are not properly stored or transported according to safety precautions and rules, they can cause both material and moral damage. In this study, a hazardous material detection and warning system using AKAZE, ORB and SIFT image feature matching techniques is developed. To test the system, a dataset of multiple hazardous material labels with different scenes and conditions was created. The performances of feature matching techniques including image processing algorithms are examined through comparative analysis. As a result of image matching, label-related features and intervention information were retrieved from the database and displayed on the system interface. Experimental results show that the ORB technique is the best method for feature matching and accurate matching, and the AKAZE technique is the fastest feature detection method.

Keywords: Image processing, image feature matching techniques, AKAZE, ORB, SIFT, hazardous materials.

Öz

Tehlikeli maddelerin taşınması güvenlik ve özel önlemler gerektiren birçok kritik durumu içermektedir. Mevzuatlar gereğince uluslararası standartları içeren tehlikeli maddeler yakından takip edilmeli ve duruma göre önceden önlemler alınmalıdır. Yapay zeka, görüntü işleme ve veri analizi teknikleri, tehlikeli maddelerin etiketlerini tanıma ve sınıflandırma konusunda kullanılabilmektedir. Bu durum acil müdahale anında erken hareket etmek için önemlidir. Eğer tehlikeli maddeler güvenlik önlemlerine ve kurallarına göre uygun depolanmazsa veya taşınmazsa hem maddi hem de manevi zarara yol açabilmektedir. Bu çalışmada AKAZE, ORB ve SIFT görüntü özellik eşleştirme tekniklerini kullanan tehlikeli madde tespit ve uyarı sistemi geliştirilmiştir. Sistemi test etmek için farklı sahneleri ve koşulları içeren birden fazla tehlikeli madde etiketinden elde edilen bir veri seti oluşturulmuştur. Karşılaştırmalı analizler ile görüntü işleme algoritmalarını içeren özellik eşleştirme tekniklerinin performansları incelenmiştir. Görüntü eşleştirmesi sonucunda veri tabanından, etiketle ilgili özellikler ve müdahale bilgileri alınarak sistemin arayüzünde görüntülenmesi sağlanmıştır. Deneysel sonuçlar ORB tekniğinin özellik eşleştirmesi ve doğru eşleme konusunda en iyi yöntem olduğunu ve AKAZE tekniğinin en hızlı özellik bulan yöntem olduğunu göstermektedir.

Anahtar Kelimeler: Görüntü işleme, görüntü özellik eşleştirme teknikleri, AKAZE, ORB, SIFT, tehlikeli maddeler.

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1. INTRODUCTION

The identification and proper characterization of hazardous substances are critical for industrial safety, public health, and environmental protection. Nowadays, hazardous material labels appear in many areas almost every day (U.S. Environmental Protection Agency, 2024). The transportation of hazardous materials involves both a challenging process and considerable risks. It is not possible to give up many tools that make our lives easier, such as cell phones, computer batteries, chemicals, gases, and explosives. These substances have become an integral part of our daily lives (U.S. Department of Transportation Federal Motor Carrier Safety Administration, 2022). Preventing or minimizing the hazards that may arise during the use and transportation of these substances requires an important area of expertise in terms of human health and the environment (U.S. Environmental Protection Agency, 2024). Accidents during the transportation of hazardous materials are usually caused by the lack of coordination, ignorance, and carelessness of employees (National Academies of Sciences Transportation Research Board and National Research Council, 2010). Some hazardous materials transported in containers can lead to incidents such as leakage, explosion, and combustion. As a result of these accidents, it is inevitable that the material being transported and the employees working in the field will be damaged. In order to prevent such accidents, solutions should be developed to increase automation and reduce manpower in the field. Because the higher the human factor in these areas, the higher the risk. In this context, measures can be taken with solution proposals on issues such as storage of hazardous substances in accordance with the legislation, rapid intervention in case of an accident, and informing the relevant persons (U.S. Department of Transportation, 2004). After employees are warned about these regulations, coordinated information on emergencies, risks, and protective actions should be provided (Fingas, 2002). Image processing techniques can be used for the detection and evaluation of hazardous substances against potential problems of hazardous substances. This is done on the dataset, which is realized by pixel-based preprocessing. An alternative approach is to analyze the images by training a machine learning model on the datasets.

This study is associated with the database within the scope of the performance of matching algorithms within image processing techniques. The target audience consists of employees transporting hazardous materials. Safe stacking and storage of hazardous materials requires knowledge of their characteristics and potential hazards (Sharifi, 2021). It is extremely important to know how to intervene if an emergency occurs during stacking and storage. Within the scope of the proposed study, a study is carried out by addressing the placement areas of hazardous substances, how these substances can be distinguished in containers, and how they require intervention. Containers have ADR (European Agreement concerning the International Carriage of Dangerous Goods by Road) and IMDG (International Maritime Dangerous Goods) Code labels showing the hazard class information of the transported substances. These labels provide information on the hazardous status of the substance and how to intervene with the hazardous substance. In this study, a database containing the hazard status of the substance and response methods is created according to these labels. Although there are not many similar studies, there are some examples in the literature on hazardous material transportation (Ellena et al., 2004; Brylka et al., 2021). The aims and contributions of the study are as follows:

- Dataset Collection and Performance Measurement: The dataset based on hazardous material labels was collected over different scenes, and the performance of the matching algorithms was evaluated.
- Image Processing-Based Approach: An image processing-based approach is proposed for the detection and feature recognition of hazardous substance labels.
- User-Oriented Interface Design: The performance of the matching algorithms was evaluated by designing a user-oriented interface based on fast information access.

The content of the study was organized as follows: In Section 2, the feature matching techniques are mentioned. Section 3 includes a literature review related to the study topic. Section 4 presents the dataset used and the proposed approach. Section 5 contains the experimental results and discussions. Finally, Section 6 summarizes the conclusions of the study.

2. FEATURE MATCHING TECHNIQUES

2.1. Working Principles of Feature Matching Techniques

Feature matching techniques are algorithms used to determine the unique features of an object in object detection. Using OpenCV's feature detection capabilities, these techniques find similar features on the image and place them in the corresponding area. This process is similar to putting the pieces of a puzzle together. While humans perform this process instinctively, for a computer to understand this process, certain features need to be searched for and found. In feature matching techniques, vertices are used as unique features. Since corners are interesting features in an image, feature detection algorithms usually start by detecting corners. The reason for using corners is that they always contain the same features in other areas. For this purpose, many techniques have been proposed using OpenCV's features. These techniques include Harris corner detection, Shi-Tomasi corner detection, BRIEF (Binary Robust Independent Elementary Features), AKAZE (Accelerated KAZE), SIFT (Scale-Invariant Feature Transform), SURF (Speeded-Up Robust Features), FAST (Features from the Accelerated Segment Test) algorithm for corner detection, and ORB (Oriented FAST and Rotated Brief). SIFT and SURF are patented techniques and are not free for commercial use. Table 1 provides detailed information about feature matching techniques. All these techniques are used for corner detection. Feature matching is performed with Brute-Force (BF) and FLANN (Fast Library for Approximate Nearest Neighbors) based matchers. BF Matcher matches each of the features and keeps track of the matches by rotating them by distance. It is slow because it looks for each point. FLANN, on the other hand, looks at the nearest neighbors and optimizes accordingly. This makes it faster than BF.

Table 1. Feature Matching Techniques

Feature Matching Techniques	**Author(s)**	**Year**	**Function**
Haris corner detection	Harris & Stephens	1988	The Harris algorithm measures the similarity of a pixel in an image in a certain direction and to an edge and uses the measured corner strength value for edge or corner detection. A corner is detected when the corner strength value is above a specified threshold and significantly different from other pixel values. It is represented as the cv2.cornerHarris() function in the OpenCV library.
Shi-Tomasi corner detection	Shi & Tomasi	1994	It includes an algorithm that works better by modifying and improving the function that gives the corner strength value in the Harris corner detector. It is represented as the cv2.goodFeaturesToTrack() function in the OpenCV library.
SIFT	Lowe	1999	It uses the Gaussian function to detect features of different scales in the image and blur them. It detects feature points using the difference of Gaussian (DoG). False values are eliminated with key points whose location and scale are determined. Gradient orientation histogram values are calculated for the key points. Descriptors and detection values are generated according to the orientation information. It is represented as cv2.SIFT_create() function in the OpenCV library.
LBP (Local Binary Patterns)	Ojala et al.	2001	It shows the intensity values of neighboring pixels around each pixel in the image in binary patterns. The binary patterns are then transformed into a histogram to obtain feature vectors. It is represented as the cv2.LBP_create() function in the OpenCV library.
HOG (Histogram of Oriented Gradients)	Dalal & Triggs	2005	By measuring edge and intensity changes in images, it generates feature vectors that identify objects. HOG features are often used in combination with machine learning algorithms such as Support Vector Machines (SVM) for object recognition and classification. It is not an efficient algorithm for large images and real-time applications. It is represented as the cv2.HOGDescriptor() function in the OpenCV library.

SURF	Bay et al.	2006	The box-filtered convolution computes scale space extrema using integral images. Using the determinant of the Hessian matrix for both scale and position, the constraints and scale of key points are determined. Many features are added at each step to increase speed. Good for blurred images and rotated images. It is slower than SIFT and optimized for use in real-time applications. It is represented as the cv2.xfeatures2d.SURF_create() function in the OpenCV library.
FAST	Rosten & Drummond	2006	In the FAST algorithm, a circle of 16 pixels is drawn around the point on the image, and the brightness of the point and the surrounding pixels are compared to find the corner point. If a certain number of pixels around the center point are brighter or darker than a set threshold, the center point is considered a corner. It is several times faster than other existing corner detectors but is not robust to high noise levels. They are not fast enough for real-time implementation. It is represented as the cv2.FastFeatureDetector_create() function in the OpenCV library.
BRIEF	Calonder et al.	2010	It uses binary patterns to detect important points in images. These patterns are created by comparing the intensities of different regions in the image. It is a particularly fast algorithm. BRIEF is preferred in real-time applications for tasks such as image matching and object recognition. It is represented as the cv2.xfeatures2d.BriefDescriptorExtractor_create() function in the OpenCV library.
BRISK (Binary Robust Invariant Scalable Keypoints)	Leutenegger et al.	2011	BRISK is a fast and computationally efficient feature descriptor that is robust to rotation and scale changes. It is suitable for real-time applications. It can sometimes produce incorrect results in noisy images. It is represented as the cv2.BRISK_create() function in the OpenCV library.
ORB	Rublee et al.	2011	ORB is a combination of the FAST and BRIEF algorithms and aims to overcome their shortcomings. It first uses FAST to find key points, then applies the Harris corner measure to find the first N points between them. With BRIEF, the patches around the key point are identified in binary. The rotation is robust to scale change and is fast and computationally efficient. It is represented as the cv2.ORB_create() function in the OpenCV library.

AKAZE	Alcantarilla et al.	2013	It is an accelerated version of the KAZE (KAZE Enhanced Zernike) algorithm. It uses a non-linear diffusion filter to detect important points in the image. It detects corner points by creating a hessian matrix with linear filtering in scale space. It is represented as the cv2. AKAZE_create() function in the OpenCV library.

There are several reasons for using the AKAZE, ORB, and SIFT methods in this study:

- AKAZE uses a non-linear filter, which provides the advantage of preserving details and accurate feature point detection. It is more suitable for real-time applications due to its fast detection capability. Since the proposed system is a real-time application, the ORB method is preferably chosen.
- ORB method is an optimized method based on speed. It gives faster results compared to SIFT and SURF. Along with speed, it also makes accurate matches. ORB, like AKAZE, performs well when evaluated in terms of rotation and scale. In the proposed study, ORB was chosen because the dataset consists of images from different scenes and different angles. Because it represents a robust method in terms of rotation and scale.
- SIFT is a good method in terms of feature matching. It is highly discriminative in terms of scale, rotation, and affine transformations. It can perform well in complex scenes. Since a good method in terms of both scene and scale will be preferred in this study, SIFT was used.
- Methods such as SURF and BRISK give very good results. However, they do not perform very well in terms of computation and memory compared to methods such as AKAZE and ORB.
- AKAZE and ORB are methods that give fast results. Speed is an important factor in real-time applications. The proposed work has to be fast because it provides simultaneous information to the user on an interface.
- BRIEF is a fast-computing method. The SIFT method is preferred because it produces detailed descriptors for complex and different scenes. SIFT was chosen because the study includes datasets from different scenes.
- The FAST method is also a method that produces fast results. However, it does not perform well according to scale or rotation. AKAZE, ORB, and SIFT are more robust in scale, rotation and affine transformations.

2.2. Advantages of Feature Extraction and Matching Algorithms

Feature extraction algorithms and matching algorithms are advantageous in image processing, machine learning, and other fields:

- Reduces data size by transforming complex structures on the image into simple and meaningful features.
- By finding the features, patterns, and corners of interesting areas in images with algorithms, it enables object detection from different angles and under different lighting conditions.
- Feature extraction algorithms perform well in changes such as rotation, scale, and reflection. This is important for object detection.

- Some feature extraction algorithms perform well in fast and real-time applications, extending the use case.
- Feature matching algorithms are generally less complex and capable of direct implementation. They can be implemented quickly in small and medium projects.
- There is no need for model training or lengthy tuning.
- Algorithms are easier to understand, interpretable, and explainable. Results are easy to interpret.

Feature matching algorithms have disadvantages as well as advantages. They are fast, computationally efficient, and easy to implement. However, high accuracy and generalization capabilities such as machine learning may not be available in some cases. This may vary depending on the subject being studied. Machine learning involves a large dataset, and a complex system with a lot of computational capacity. Which method to use depends on the requirements of the application, the dataset and the available computational resources. Since the proposed work does not consist of a very complex process, using image processing techniques was deemed appropriate for this system.

3. LITERATURE REVIEW

There are many academic studies and applications for the use of feature matching techniques on different datasets in different fields. Recently, there have been many studies in the literature that aim to improve target detection and recognition processes using image feature matching techniques. These improvement efforts aim to increase the detection accuracy and reduce the completion time of the study.

Tareen and Saleem (2018) reviewed different techniques for feature matching algorithms. They used SIFT (Lowe, 1999), SURF (Bay et al., 2008), ORB (Rublee et al., 2011), KAZE (Non-linear Scale-Space Feature Detection) (Alcantarilla et al., 2012), AKAZE (Alcantarilla et al., 2013), and BRISK (Leutenegger et al., 2011) as feature matching techniques and evaluated the performance of each of them. The results showed that ORB, BRISK, and SURF techniques are capable of detecting more features than the others. In addition, SIFT, SURF, and BRISK are less variable in terms of scale and perform better, while ORB shows less scale variation. In terms of speed, AKAZE, KAZE, SIFT, ORB, BRISK, and SURF obtained the results in order from fastest to slowest. Kamel et al. (2020) pointed out the shortcomings of feature matching techniques in previous studies and proposed a hybrid method. They conducted separate experiments on ORB, BRISK, AKAZE, SIFT, and SURF feature descriptors and presented the comparison results. In the studies performed on the SRM dataset, the ORB algorithm had the fastest execution time, followed by the BRISK algorithm. SIFT algorithm detected the most keypoints, while AKAZE detected very few keypoints. In the Airport dataset, the BRISK algorithm has the fastest execution time, while the SURF algorithm is the slowest. In the hybrid study, the ORB-BRISK pairing performed better, while AKAZE-SURF was the slowest and did not perform well. Tareen and Raza (2023) evaluated the potential of 14 feature detectors and 10 feature matchers, including SIFT, SURF, KAZE, AKAZE, ORB, BRISK, AGAST (Adaptive and Generic Accelerated Segment Test), FAST, MSER (Maximally Stable Extremal Regions), MSD

(Maximally Stable Disjoint Regions), GFTT (Good Features To Track), Harris Corner Detector based GFTT, Harris Laplace Detector, and CenSurE. The results showed that SIFT outperformed SURF in detecting large feature matches with low parameter thresholds. AKAZE detected fewer features than KAZE in all 10 scenes. The overall ranking was MSD, MSER, CenSurE, FAST, AGAST, SIFT, ORB, BRISK, GFTT, GFTT-H, KAZE, AKAZE, SURF, and Harris-L. These results were evaluated separately on invisible dusty, smoky, dark, noisy, blurry, sunny, shadowy, and close-up images in a variety of environments. SIFT was found to perform well for most scenes, while MSD, MSER, SIFT, KAZE, GFTT, and CenSurE were found to be good at high keypoint selection Comparative studies in the literature differ according to the subject matter. For example, Oad et al. (2022) focused on brain images and showed comparative performance metrics of brain hemorrhage status with matching methods. Ihmeida and Wei (2021) performed performance evaluations using matching methods on remote sensing images. Similarly, Forero et al. (2021) comparatively tested matching methods on multispectral images for rice crop detection. Working on noisy images, Kortli et al. (2018) showed that ORB works fast and SIFT performs better. They also pointed out that the two methods are approximately similar in terms of matching. Apart from matching methods, artificial intelligence methods have also been applied to improve the performance of hazardous substance labeling detection by applying artificial intelligence methods to noisy data (Brylka et al., 2021). During the evaluation, it was observed that the success criteria of the matching algorithms differed depending on the topics studied. The parameters may vary depending on the study situation and affect the performance of the matching methods.

Clear and accurate labeling of hazardous materials can help prevent potential accidents. Separation of items that can and cannot be stored next to each other and careful control of check-in and check-out processes are important to minimize risks. Damage records should be checked meticulously. These controls and transportation processes are carried out with special training (Brylka et al., 2021). The new technologies developing today should be taken into account in addressing these issues related to hazardous materials. In this work, a fully automated approach for various detection and analysis tasks is presented. The transportation and labeling of hazardous materials are based on international global standards (UNECE, 2024). Each country develops solutions for its own transportation within the framework of internationally standardized rules. Lu et al. (2019) compared the relevant rules of the International Maritime Organization (IMO) with the existing rules and standards in China and presented the results in a table. The U.S. Department of Transportation Pipeline and Hazardous Materials Safety Administration has a database of US safety information that is kept up-to-date by analyzing the statistics of incidents involving hazardous materials by year (U.S. Department of Transportation Pipeline and Hazardous Materials Safety Administration, 2022). Access to all and many statistical data is provided. Another study examining the effects of hazardous material transportation in Thailand analyzes and evaluates the data obtained through field work and provides recommendations on the current situation (Watcharejyothin et al., 2022). Literature studies on hazardous materials show that it is a very important area that requires attention.

The proposed work is realized within an interface. Previously, Ellena et al. (2004) developed a system for the detection of trucks carrying dangerous goods. This system evaluates the labels on the truck according to the hazardous material label and labels them as hazardous on the interface. As a result of the studies on matching methods in the literature, our current study aims to match hazardous material labels between images simultaneously and display the emergency response measure information stored in the database on the interface. The proposed work also shows the performance parameters of the matching methods on the interface. The image data contains different backgrounds and was evaluated by giving parameter values according to these different backgrounds. Thus, it was aimed at obtaining a more general result.

4. DEVELOPED HAZARDOUS MATERIAL DETECTION AND WARNING SYSTEM

In this study, AKAZE, ORB, and SIFT feature extraction algorithms were used to detect hazardous substance labels. These algorithms were chosen to identify the unique features of the labels and to accurately detect the labels using these features. The detected hazardous substance labels are matched with the relevant database information and provide the user with information for warnings and precautions. This model was based on success comparisons using feature matching to accurately detect hazardous material labels. Hazardous materials need to be transported and stored safely. The performance of the model was evaluated using various metrics. Particular attention was paid to speed and matching points. The dataset used images taken under various backgrounds and conditions.

The dataset, which constitutes the main source of the study, was tested for different methods in the interface program. Method successes and performances were obtained, and the results were detailed under other headings. All these operations were performed on an interface designed by a Qt designer. First, the test data is selected, then the folder containing the training data is selected, and the matching result parameters and run time information are displayed on the screen.

4.1. Dataset Description

The dataset used for the study consists of Google images and a structure used for an article. This dataset was used for hazardous material detection and database mapping. The data in the database include the emergency response situations caused by the hazardous substance and the properties of the hazardous substance. Hazardous material labels appear in various fields of our daily lives. These labels, in different formats and with international standards, are used in port, road, rail, and, to a lesser extent, air transportation. Hazardous material labels are of great importance today in terms of safety and security, both in robot rescue systems and in reporting the dangerous status of materials transported by humans. Image processing, computer vision, and artificial intelligence methods play an important role in the detection and recognition of such important labels and the creation of an intervention warning system. In this study, a comparative warning system was created based on matching algorithms used in image processing.

This system should basically provide the key features created in the database. Also, it should be measured to see how it reacts when the images vary in terms of their size and attribute characteristics. In terms of requirements, the dataset collected basically meets the needs within the scope of the research topic. It provides a scientific contribution to the identification and matching of hazardous substances.

4.1.1. Data collection

This study was created by selecting images expressing hazardous substance labels from Google Images and collecting them from the websites where the datasets are available (Mohamed et al., 2018). The dataset consists of data with different backgrounds and taken from different angles. In total, 600 images were collected. The background consists of hazardous material labels placed on sawdust surfaces, wooden structures, and brick wall structures. The images obtained from Google Images include images with labels on containers and images with hand-held labels. The dataset is based on 8 different types of flammable materials. All images are high resolution (5184x3456), with different lighting conditions (dark, light), and blurred. The images were obtained by creating different scenarios (Mohamed et al., 2018). The performance of the methods presented in the related study on the collected data was evaluated. Before using the raw data directly, certain image preprocessing methods were used to output the proposed methods. This is because cleaning the areas that are not considered important in the images to get better results from the images has a positive effect on the method. The images were converted to black-and-white images. Table 2 gives an overview of the dataset collection.

Table 2. Dataset Collection Overview

Session	Image	Quantity
1	Hazardous Material Labeling Dataset	600
2	Google Images	100

4.1.2. Data preprocessing

Within the scope of the study, certain image processing steps were applied to each method without performance evaluations. After pre-processing, each image taken from the test data was matched using matching algorithms on the training data. The matched image was retrieved from the database, and its information was reflected on the interface system. The splits for the training and test datasets to be used for the warning system are presented in Table 3. It was resized to 225x225 pixels for matching images. The collected dataset was divided into training (83%) and test (17%).

Table 3. Dataset Splits for Train and Test

Task	Train Samples	Test Samples
Label matching	500	100

4.2. Breakdown of the Tasks

Within the scope of the study, depending on the matching algorithms on the interface program, information based on emergency response situations is retrieved from the database and displayed simultaneously on the interface. AKAZE, ORB, and SIFT matching methods were preferred in the system. In order to find images similar to the image given as each test data and to determine the characteristics of hazardous materials, the relevant response information for hazardous materials is extracted from the database depending on the UN (United Nations) number and reflected on the screen. The parameters of the three methods were tested, and the best matching parameters and threshold values were determined. Figure 1 shows the overall flowchart of the designed and pro-posed system.

4.2.1. Models and algorithms

In the image processing process, we focused on AKAZE, ORB, and SIFT matching methods based on the OpenCV library in Python programming language. AKAZE is an algorithm for find-ing specific features in an image. Alcantarilla et al. (2013) presented the AKAZE algorithm by im-proving the KAZE algorithm (Alcantarilla et al., 2012). This algorithm is based on nonlinear diffu-sion filtering. It produces more efficient results with Fast Explicit Diffusion (FED) in AKAZE. The descriptor of AKAZE is based on the Modified Local Difference Binary (MLDB) algorithm and the determinant of the Hessian Matrix, which is also highly efficient (Tareen & Raza, 2023).

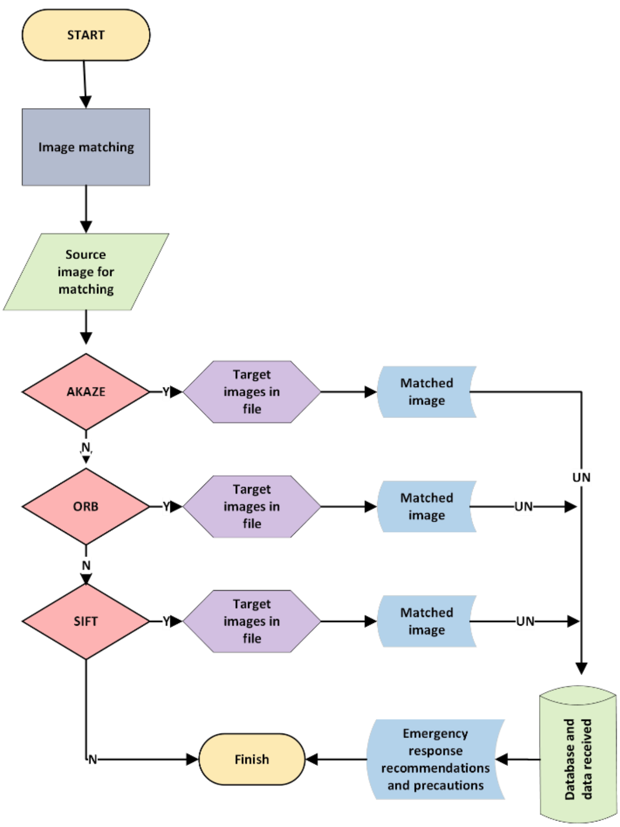

Figure 1. Flowchart of the Developed System

Lowe (1999) introduced the SIFT method, which has been used in many studies. The SIFT detec-tor is based on the DoG operator, an approximation of the Laplacian-of-Gaussian (LoG) (Tareen & Raza, 2023). It finds and detects local maxima in images of various scales using DoG. However, its disadvantage is its high computational cost.

Rublee et al. (2011) presented a method called ORB. It first detects key points in images using the FAST algorithm and then calculates BRIEF apertures around these key points. It detects FAST corners at each layer of the scale pyramid and evaluates the corners of the detected points using the Harris Corner score to filter out the highest quality points (Tareen & Raza, 2023). ORB features are independent of scale, rotation, and limited affine changes. It is the fastest and most efficient algorithm. ORB works faster than SIFT and SURF and is especially suitable for real-time applica-tions and resource-limited systems. The general flowchart of the matching algorithms implemented on the interface is shown in Figure 2.

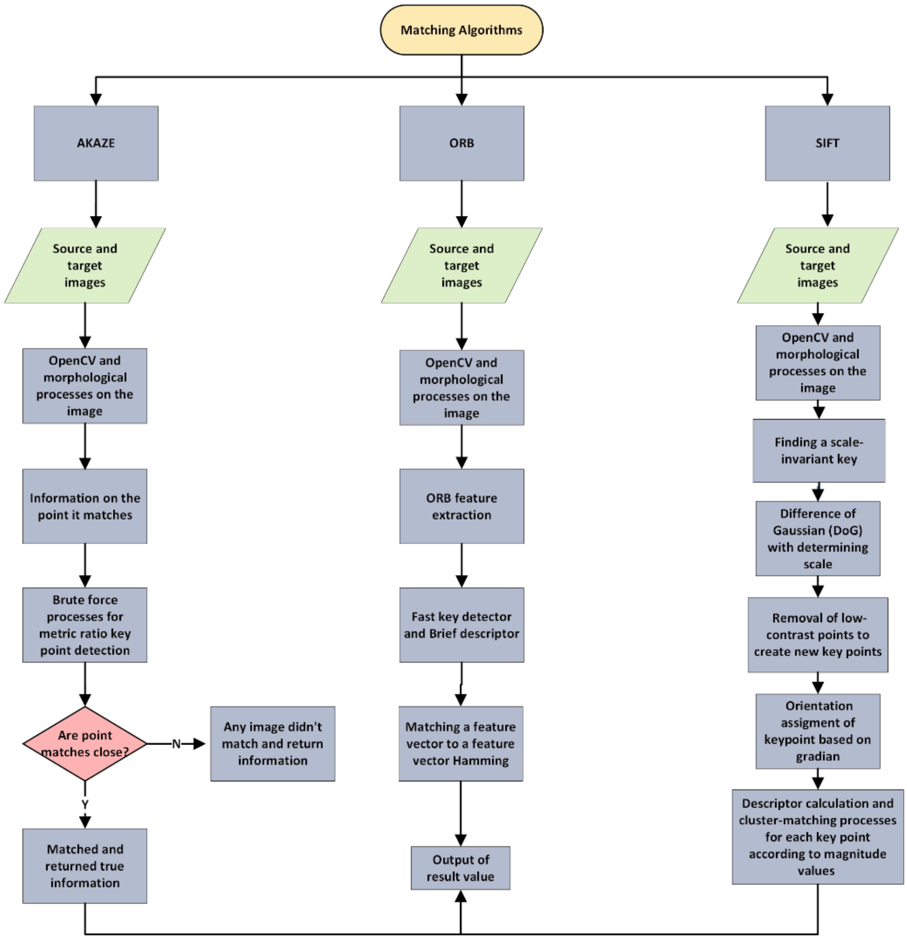

Figure 2. General Flowchart of Matching Algorithms

These methods are widely used in computer vision applications. They are frequently encountered in tasks such as object recognition, image matching, 3D modeling, and motion analysis. Each method has advantages and disadvantages. Which one to use depends on the requirements of the applica-tion, the computational power, and the characteristics of the dataset. The parameters used in these methods are given in Table 4. In the AKAZE method, BruteForce is calculated using the Hamming distance relation. Hamming distance calculates the number of different bits between two attribute vectors. Hamming distance is usually used on binary attributes (e.g., ORB, BRIEF). With the near-est matching method, the number of neighbors between two images is determined. For the pro-posed work, this value is taken as two. This returns the two closest matching points for each refer-ence point. The nearest neighbor matching ratio is set to 0.8. This ratio is considered the threshold for whether matching points will be retrieved when using the nearest neighbor matching algorithm. It prevents situations that can sometimes be caused by false matches. If the given ratio is greater than the resulting ratio, the matching is accepted. The inlier threshold was given a value of 2.5 as a distance threshold used to determine the inlier points with homography control. Homography de-scribes the perspective transformation between two different images.

If the average matching value after matching is greater than 49, the match is considered correct. This value is determined by testing images within the system. In the ORB method, the BruteForce value is determined using the Hamming norm. Cross-validation is performed with the value, and if the resulting matching score is greater than 108, the match is considered correct. In the SIFT meth-od, BruteForce is calculated using Norm-L2. Cross-validation is performed, and if the resulting value is greater than 108, the match is considered correct. Table 4 shows the parameters and values used in the system.

Table 4. Base Model Information for the Classification Task

Method	**OpenCV's Constructor Settings**
AKAZE	cv2.AKAZE(cv.DescriptorMatcher_BRUTEFORCE_HAMMING, knnMatch(desc1, desc2, 2), match_ratio = 0,8, inlier_threshold = 2.5,Match>=49) (OpenCV, 2024a).
ORB	cv2.ORB(cv2.BFMatcher(cv2.NORM_HAMMING, crossCheck = True), Match>= 108) (OpenCV, 2024b).
SIFT	cv2.SIFT(cv2.BFMatcher(cv2.NORM_L2, crossCheck=True), Match>= 108) (Tareen & Saleem, 2018)

After the method outputs, a matching process was performed on a simple database created in advance. The unique identifiers of the hazardous substances were determined, and the tables were linked to each other. Important warning information such as physical and chemical information about hazardous substances, safety warnings, first aid information, what to do in case of emergency, compatibility information of hazardous substances with other substances, and cleaning of hazardous substances were recorded in the database. The data model was designed according to this information and a useful design was created. Data information was entered into the system by considering the data query situation. According to the uniquely selected UN number, access to the database is made, and querying and feature matching is performed. All these situations are realized simultaneously on the interface, and the information is reflected in the relevant fields on the interface.

4.2.2. Evaluation metrics

Evaluation of matching algorithms involves the use of various metrics. Firstly, the accuracy of the algorithms is measured using the accuracy metric, which determines how accurately the algorithms perform matching on a specific application or dataset. Accuracy is calculated based on the images and matching values simultaneously reflected in the system. Values higher than the given matching value for each method indicate the correctness of the match. However, sometimes a match may appear to be correct but may not actually reflect the matched value, making the match unacceptable. In this case, the system compares the images considered to be matched with the actual images, and when there is a false match, these images are labeled as unmatched. Accordingly, the average accu-racy value is calculated for each method.

The speed metric expresses the processing time of the methods simultaneously running on each image. In the proposed study, the total processing times for feature extraction and matching are evaluated separately for each image and method, and the average processing time is calculated. Pro-cessing speed evaluations are based on the time spent on each image. The processing power of methods is directly proportional to speed.

The repeatability metric measures whether the same features can be correctly identified in different images. This was tested and evaluated on the proposed system by providing images taken in differ-ent scenes. The evaluation of noise resistance involved assessing the results obtained from the im-ages against noise.

5. EXPERIMENTAL RESULTS AND DISCUSSION

Feature matching methods are applied in various fields, and some applications are of critical im-portance. In this study, the effects of AKAZE, ORB, and SIFT feature matching methods on haz-ardous material labels are evaluated. The accuracy metrics are measured by taking into account the evaluation metrics given earlier, and the results are presented in Figure 3 and Table 5. The collected dataset was divided into training (83%) and test (17%) images, and matching methods (AKAZE, ORB, SIFT) were applied. The results were meticulously evaluated. The AKAZE method showed an average accuracy of 33%, the ORB method showed 91%, and the SIFT method showed 68%. The ORB method achieved the highest performance, demonstrating its efficiency. It resulted in a 9% error rate by matching with too many points and considering those matches as correct, exceed-ing the threshold. Additionally, the average execution times are presented in Figure 3. Although AKAZE has the fastest processing time, it produces incorrect results. The processing time for SIFT is considerably long.

Overall, when error rates were evaluated, it was observed that the error rate increased when scene conditions changed, along with an increase in processing power. It was also noted that matching algorithms alone were not sufficient for images taken in noisy environments. ORB and SIFT per-formed almost equally well in noisy images. When the results were evaluated, AKAZE showed the lowest performance. AKAZE provides more accurate feature detection by using nonlinear diffusion filters. However, the computational cost and performance may decrease. The ORB algorithm shows the highest performance. ORB is fast and robust to rotation and scale changes. SIFT showed moderate performance. SIFT's strengths are robust to scale and rotation but limited in computational cost and speed.

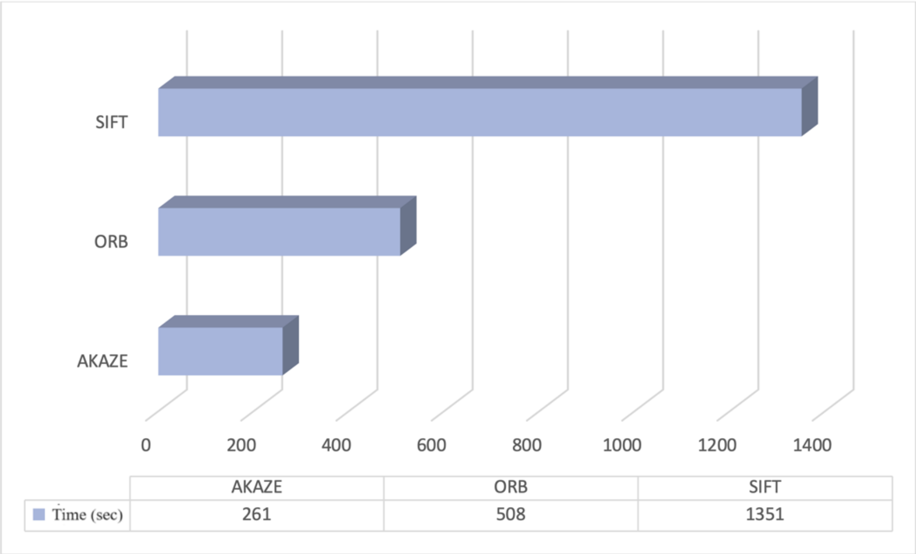

Figure 3. Execution Time Graph of AKAZE, ORB, and SIFT Methods

Three different matching methods were used for the classification of hazardous material labels. These methods enabled the identification of hazardous material properties and provided representa-tion in the system for intervention measures. The accuracy results are presented in Table 5.

Table 5. Accuracy Results for the Classification Task

Base Model	**Accuracy**
AKAZE	33%
ORB	91%
SIFT	68%

According to the results in Table 5, ORB demonstrated high performance by matching the most features and achieving accurate matches. While AKAZE showed lower performance in terms of feature matching and accurate matching, it performed well in terms of speed. When evaluating the results, it is observed that as scene conditions change, feature matching and performance decrease, resulting in a decrease in the matching ratio. These observations align with the findings from the literature review. Two main issues related to feature matching have been identified:

- Scene diversity: It reduces feature matching in matching methods and decreases the number of features. To address this issue, accuracy can be improved by adjusting parameter values and expanding them with new values.
- Noisy environment: In such environments, matching results vary when the object threshold decreases. Preprocessing the image and adjusting the parameters used in matching can pro-vide a solution to this issue.

Figures 4 and 5 show the interface screens of the developed system. Figure 4 shows the interface where the labels collected and created for hazardous substance detection are detected. Figure 5 shows the classification and warning interface screen, where the results of matching the label de-tected in Figure 4 with the database are displayed on the screen. In Figure 4, images and the feature matching method are selected to extract information from the image. There is also a time counter here. In Figure 5, there is a separate button for each warning. Whichever information is needed, the information is reflected on the screen by pressing the button.

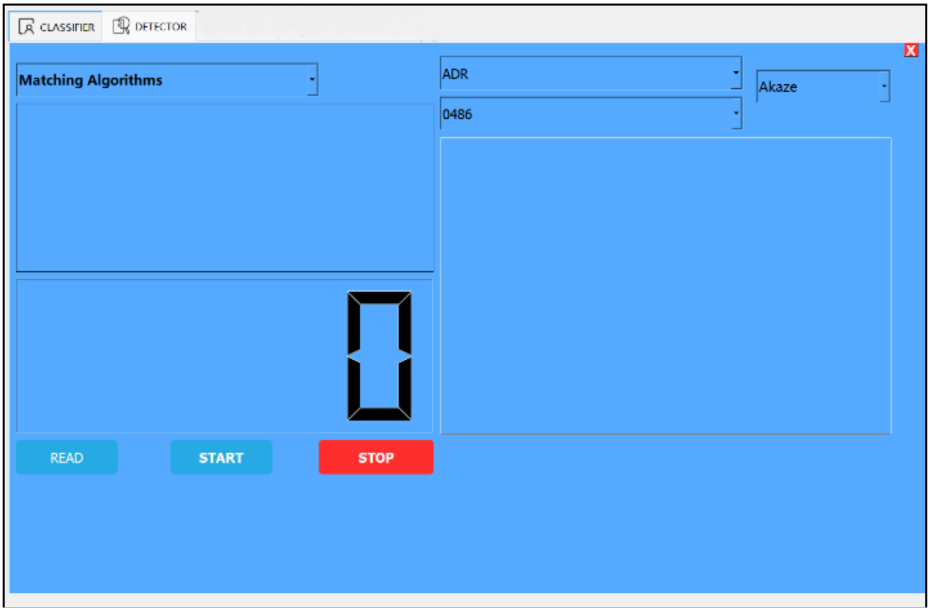

Figure 4. Label Detection Interface Screen

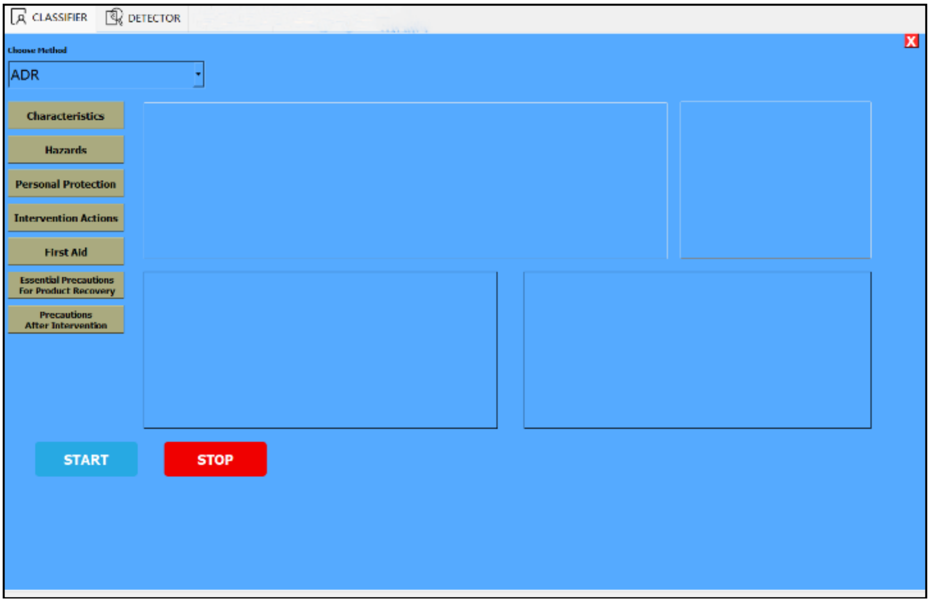

Figure 5. Classification and Warning Information Interface Display

6. CONCLUSION

This study focuses on the utilization of a dataset collected for the detection of hazardous material labels and the application of matching methods. The matching results are compared and evaluated against the features and intervention data concurrently retrieved from the database. This compre-hensive research underscores the contemporary significance of hazardous materials and contributes to a systematic understanding of image processing techniques for their detection. Performance analyses conducted on the dataset containing various scenes and noise data present a comparative performance of matching methods and feature-intervention information in the database. In future studies, the integration of these label systems with barcode technology to transform them into ro-botic systems is recommended. This is crucial for reducing human intervention in hazardous mate-rial transportation and introducing semi-automatic systems to our country.

While the current system covers a section of transportation, it is envisaged to form a chain of inter-connected systems that will create a seamless and integrated network. Representing the next level of comprehensive hybrid technology, the system is expected to seamlessly integrate with the exist-ing framework in today’s transportation.

Contribution of The Authors
The authors confirm that they equally contributed to this paper.

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Conflict of Interest
The authors declare that there is no conflict of interest.

Statement of Research and Publication Ethics
Research and publication ethics were observed in the study.

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