Enhancing aerial image registration: outlier filtering through feature classification

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ABSTRACT

In the context of feature-based image registration, the crucial task of outlier removal plays a pivotal role in achieving precise registration accuracy. This research introduces an innovative binary classifier founded on an adaptive approach for effectively identifying and eliminating outliers. The methodology begins with the utilization of the scale invariant feature transform (SIFT) to extract features from two images, initially matched using the Euclidian distance metrics. Subsequently, a classification procedure is executed to segregate the feature points into two categories: genuine matches (inliers) and spurious matches (outliers), which is accomplished through the brute-force matcher (BFM) technique. To enhance this process further, a novel classifier rooted in the random forest algorithm is introduced. This classifier is trained and tested using a comprehensive dataset curated for this study. The newly proposed classifier plays a pivotal role in attenuating the influence of outliers, ultimately leading to refined image registration process characterized by enhanced accuracy. The effectiveness of this outlier removal approach is assessed through a meticulous analysis of positional and classification accuracy. Additionally, we offer comparative insights by evaluating the performance of selected algorithm on our dataset.

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1. INTRODUCTION

Image registration processing is the task of finding the feature transformation, which is mapped in a specific space to its position in another space. Image registration allows a single transform information process between two spaces, i.e., the basic steps of image registration algorithms always involve the extraction of features, the definition of geometrical transformation, similarity measure, and enhancement. Image registration is a geometrical or spatial transformation process that aligns interested points in two or more images that are taken by different sensors or different viewpoints at different times. The image registration process is composed using two sources of images, including the reference image, which is regarded as a basis for another image (i.e., sensed image or source image). Although numerous state-of-the-art techniques of image registration in aerial images have been developed, most of these techniques are not robust in the matching process. For instance, in this part of the work, the brute-force matcher (BFM) which used with scale invariant feature transform (SIFT) features, often makes mistake in the matching process and produce outliers in the matched images which impact on image registration process. According to that, a problem arises when we use the SIFT with the BFM algorithm, which could affect the accuracy of the matching process. Thus, we addressed this problem by using a classification algorithms technique to proposing a new adaptive binary classifier-based approach of remove outliers after the matching process. Therefore, we can obtain an accurate image registration which can be used in change detection processing through using classification algorithms and conducting the enhancement process.

There are two approaches of image registration, i.e. conventional and deep learning approaches. Both approaches are essentially used for area-, feature-, and hybrid-based image registration. Area-based analyzes image intensity patterns for full image registration. Feature based identifies and matches features, while hybrid method combines area and feature based techniques. The feature-based registration extracts feature and aligns images through transformation [1]. Image registration aligns images by determining geometric transformations (scale, rotation, translation). Crucial in image analysis for data fusion, including change detection and restoration [2]. Widely used in remote sensing (e.g., mosaicking and change detection), medicine (e.g., medical image fusion and tumor monitoring), and computer vision.

One of the major issues of image registration is the images can be captured from different angles. This issue has a major impact on the performance of the registration techniques. Onyango *et al.* [3] proposed a new technique to address this issue by using the AKAZE algorithm. However, the proposed solution is highly dependent on the captured images which means the exclusion or removal of any image from the dataset can lead to a high impact on the registration process. In addition, the proposed solution is highly dependent on human interaction, which is a subjective issue and may require a highly skilled person.

Zhao *et al.* [4] introduced a system that uses the SIFT algorithm for multispectral/multidate remote image registration, named “robust Delaunay triangulation matching (DMT)”. The system involves improved SIFT for one-to-one matches, DTM for comparing Delaunay graph structure, recovery of inliers removed during DTM iterations using Voronoi diagrams from Delaunay graphs. However, the systems feature point validation is limited to local graph structures. It was tested on 50 image pairs with overlapping areas, selected based on different band combinations.

Koch *et al.* [5] presented an innovative image registration method using new feature point detectors, SIFT descriptors, one-to-many matching, and geometric verification with pixel-distance histograms. This technique is tailored for registration nadir unmanned aerial vehicles (UAV) and aerial images, with the aerial images taken at a 1000-meter altitude and the UAV images captured at altitudes between 80 and 120 meters. Evaluation showed that the proposed method outperformed SIFT and A-SIFT in image registration.

Jende *et al.* [6] introduced a novel image registration technique for high-resolution aerial nadir images in mobile mapping. They adapted the Forstner operator to identify feature key points in aerial ortho-images and applied these key points to the images. They claimed a 90% precise correspondence due to fewer outliers. However, their technique faced challenges like radiometry variations, diverse perspectives, and illumination differences. It could only detect feature key points in a single image and couldn’t handle uncertainties caused by repetitive image patterns.

Wang *et al.* [7] proposed a powerful deep neural network for remote sensing image registration. The authors paired patches from the remote sense and reference images and then learned the map of these pairs to register the images. Furthermore, they reduced the computational time and improved the registration accuracy of the technique. Finally, the authors tested the proposed technique with seven image sets from Radarsat, SPOT, and Landsat. They increased registration accuracy from 2.4 to 53.7%. Feng and Feng [8] proposed an image registration technique that handles intensity and geometric transformations. They introduced two novel assessment factors, “salience correlation” and “parsimony,” to evaluate alignment accuracy. They claimed their technique is adaptable, dynamic, and computationally efficient, but its accuracy and efficiency vary depending on the specific application. It lacks robustness in mapping compared to feature-point-based methods due to challenges in point-point correspondence determination caused by image degradations.

According to Yang *et al.* [9], a new registration algorithm for multi-temporal remote sensing images, which are used in various military and civilian applications. They emphasized how changes in the ground surface affect feature point detection in image registration algorithms, leading to the disappearances of inliers and an increase in outliers by using convolutional neural network (CNN). Their technique also enhances registration robustness by increasing the number of inliers. The evaluation was applied to 15 image pairs from two datasets. They argued that their technique outperforms the SIFT technique in terms of accuracy. However, they acknowledged several limitations, including limited handling of outliers, difficulty with high-resolution images, a shortage of training data, challenges in assigning recursive levels of nearest neighbors, and high computational time.

2. MOTIVATION

Several aerial images registration techniques that are mainly focus on region of interest (ROI) and the features of the image could not proof their high capability to highlight or at least preserve the information richness of the aerial image. The drawbacks of the state-of-the art techniques, and the limitation of BFM are motivated this research to register the captured aerial images without geographic information by one of most robust classification algorithms (random forest (RF)) based collected datasets for testing and training as anew classifier to identify the change of the two images that are captured in different time of the same geographical area. Therefore, the high performance and superior capability of learning techniques such as the deep learning led the researchers to hybridize the image change detection conventional techniques with learning techniques to register the aerial images and produce a pleasant with high accuracy resultant image.

3. METHOD

The methodology of this study shows the main steps that followed in image registration. We used the SIFT to detect and compute key-points from the captured images in Iraq. Then the similarity is measured using a BFM to match the descriptors of the key-points. For the registration process to be effective, we need to eliminate the outliers. A new classifier model is developed, and it can use this learned classifier to classify two binary classes that refer to a positively matched descriptor (PMD) and negatively matched descriptors (NMD). Finally, the registration processing is performed using the PMDs after removing or reducing the NMDs. Figure 1 shows the general flow chart of the proposed methodology that followed.

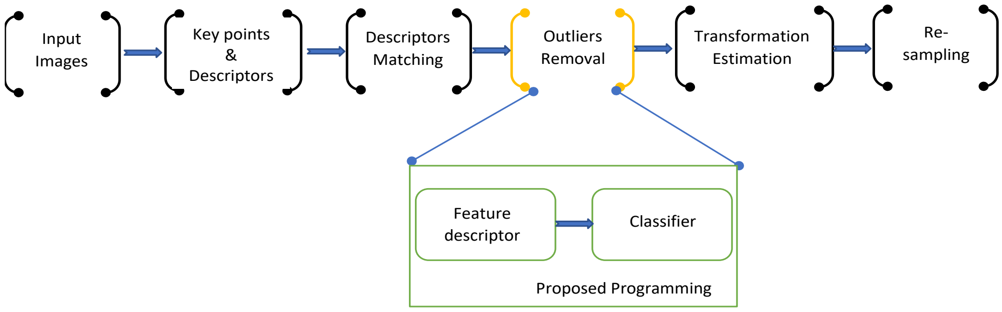


Figure 1. The flow chart of image registration steps

3.1. Scale invariant feature transform

In 2004, the University of British Columbia, particularly David G. Lowe, was the first to build the SIFT algorithm. SIFT uses the images to extract features for matching based on different landscape scenes and compute their descriptors [10]. First, in computer vision and photogrammetry, the SIFT became a standard technique. SIFT works with scale space that is derived by convoluting the image with the Gaussian kernel [11]. In the difference of Gaussian, the extrema of SIFT constitutes two descriptors. The four main steps involved in the SIFT algorithm are as follows [12].

- Key-point detection: in this stage, the operation of key-point detection is represented by identifying the locations and scales that can be frequently assigned under multi-views of the exact object. First, SIFT detects the locations, which are invariant with the image size.
- Key-point localization: the key-points generated by the previous step produce many other key-points. Some are located along the edge and the rest do not have appropriate contrast. In both cases, they would not be useful as a feature and thus need to be discarded.
- Orientation assignment: key-points have been obtained where they have been tested for stability. Essentially, we know the scale of key-points detection, so the scale invariant is kept. Then, we need to assign the orientation for each key-point to be with rotation invariant.
- Feature descriptors generation: for each key-point, it will compute the descriptor in the region of the local image under the variations. It takes a window around each key-point with 16×16, and it is divided into 16 sub-blocks with a size of 4×4. In each sub-block, the creation of orientation histograms with 8 bins is performed. Thus, the directions with 4×4×8 will give us 128 bin values.

3.2. Brute-force matcher

Briefly, BFM is a good approach for a large dataset that consists of the descriptors, it takes a single feature descriptor in the first image and matches it with all feature descriptors in the second image depending on the distance measure [13]. BFM returns the closest descriptor after using a type of matching distance calculation, such as Hamming distance measurement, which is used with oriented fast and rotated binary robust independent elementary features (ORB), binary robust independent elementary features (BRIEF), binary robust invariant scalable keypoint (BRISK), and Euclidean distance in the case of SIFT and for speeded-up robust features (SURF) when it is robust [14]. The two optional parameters in BFM are NORM_L2 and NORM_L1, which can illustrate the mathematical terms in (1) and (2), respectively. NORM_L1 is the summation of absolute values:

$$|x|i = \sum_{r=1}^{n} |\overset{r}{x}| \tag{1}$$

Whereas, NORM_L2 is Euclidean distance (square root of summation the squares):

$$|x| = \sqrt{\sum_{t=1}^{n} |\overset{t}{x}|} \tag{2}$$

4. PROPOSED METHOD

The pipeline of our proposed shows the image registration process. All the key-points and descriptors are collected from the images and the matching process is performed, so the datasets are constructed and labeled. For a typical registration process, we have to remove or reduce the outliers resulting from BFM. A new classifier is developed, and this classifier will learn to be ready to remove or reduce the outliers from the prepared new dataset. In the subsequent subsections, we will explain in detail the methods of the proposed.

4.1. Key points and matching

Key-point detection is followed by matching using a similarity measure. The block-based approach is favored the non-block-based approach due to its lower complexity and enhanced correspondence through geometric considerations [15]. Figure 2 shows positively matched key-points in the BFM over the same geoinformation area, whereas Figure 3 displays negatively matched key-points (outliers) across different geographical areas.

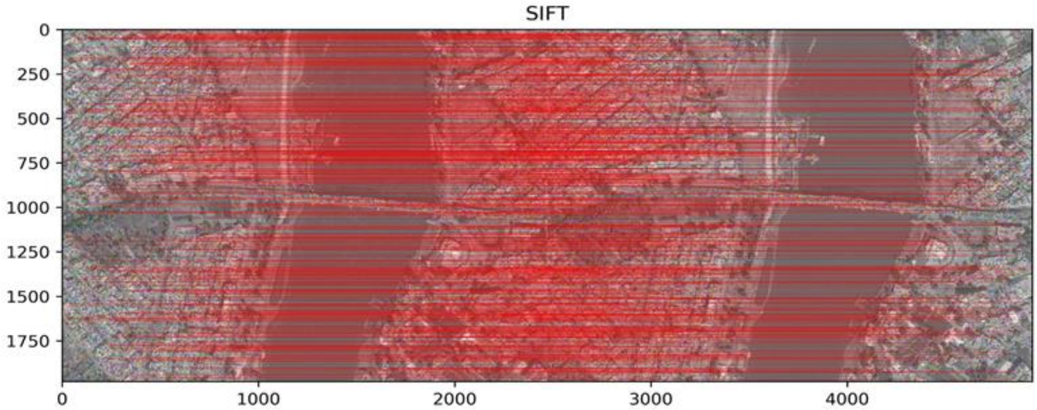


Figure 2. Brute-force correct matches for two same geographical

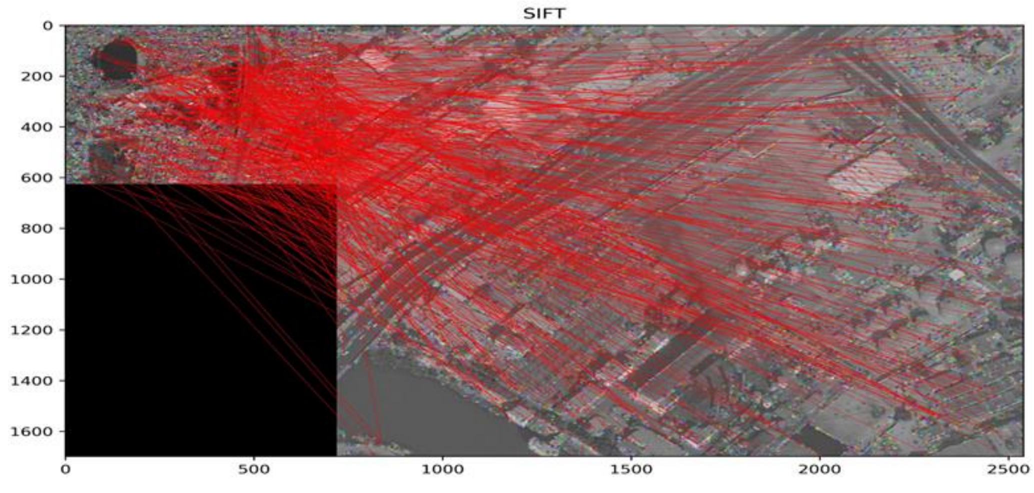


Figure 3. Brute-force incorrect matches for two different geographical

4.2. Classifier adaptive outlier removing

In this step, our main objective is to develop a new classifier based on outlier removal methods. The first challenge was to collect the dataset, we were able to obtain a single cross-section of Baghdad City through the assistance of the Iraqi survey authority (Figure 4). Our newly proposed pipeline is divided into data collection and preparation, adaptive classifier training, and classification modules for inliers and outliers.

Figure 4. Baghdad City

4.2.1. Data collection and preparation

First, in the schema of our newly proposed to remove outliers, the vector information of features is constructed. The dataset is labeled, "true" label for the PMDs and the "false" label for the NMDs. The dataset structure was formed from 560,000 for both true and false records, which means we can collect 1120000 records. In general, the SIFT algorithm can extract the feature points with descriptors, each descriptor is a vector of a real number consisting of around 128 dimensions of the feature vector [16].

4.2.2. Adaptive classifier training

This module contains two phases, the first phase is importing the parameters for necessary arithmetic and libraries, which are suitable for the training process and mathematical operations. In the second phase, we used some of the fitness functions that play an important role in building, learning, and choosing the appropriate classifier among a set of classification algorithms depending on the results of the training and testing process for the experimental step (Figure 5). Once all data points are classified in the training, it will be easy to compute the true positive (TP), false positive (FP), false negative (FN), and true negative (TN) [17].

4.2.3. Classification

Once the classifier model is built and completes the training and testing processing steps, the classification of inliers and outliers becomes straight forward. We used the appropriate steps to collect new images. The SIFT algorithm is used to extract the key-points and apply the BFM for the matching process. Then, feature descriptors for every matched key-point are constructed. To implement our classifier model, we used Python and Jupyter platform on a 64-bit windows system with CPU intel iris and 8 GB of RAM.

4.3. Experiment classifier setup

Achieving this main goal depends on the results that we derived by computing the confusion matrix, area under receiver operating characteristic (AUROC), classification report, and accuracy score. Before entering into the details of our model experiment, we need to be concerned about these values that are important in the evaluation of our classification model.

4.3.1. Confusion matrix

The confusion matrix is regarded as a visual tool in models' evaluation. Being a matrix, the overall design consists of columns that represent the results of the prediction class, and rows that represent results of the actual class as a 2×2-dimension [18]. We can note the entries of the confusion matrix (TPs, FPs, FNs, and TNs) as follows:

- TP: positive examples of numbers correctly classified as positive by the model.
- TN: negative examples of numbers correctly classified as negative by the model.
- FP: positive examples of numbers incorrectly classified as positive by the model (i.e., negative examples wrongly classified as positive). FN: positive examples of numbers incorrectly classified as negative (i.e., positive examples wrongly classified as negative).

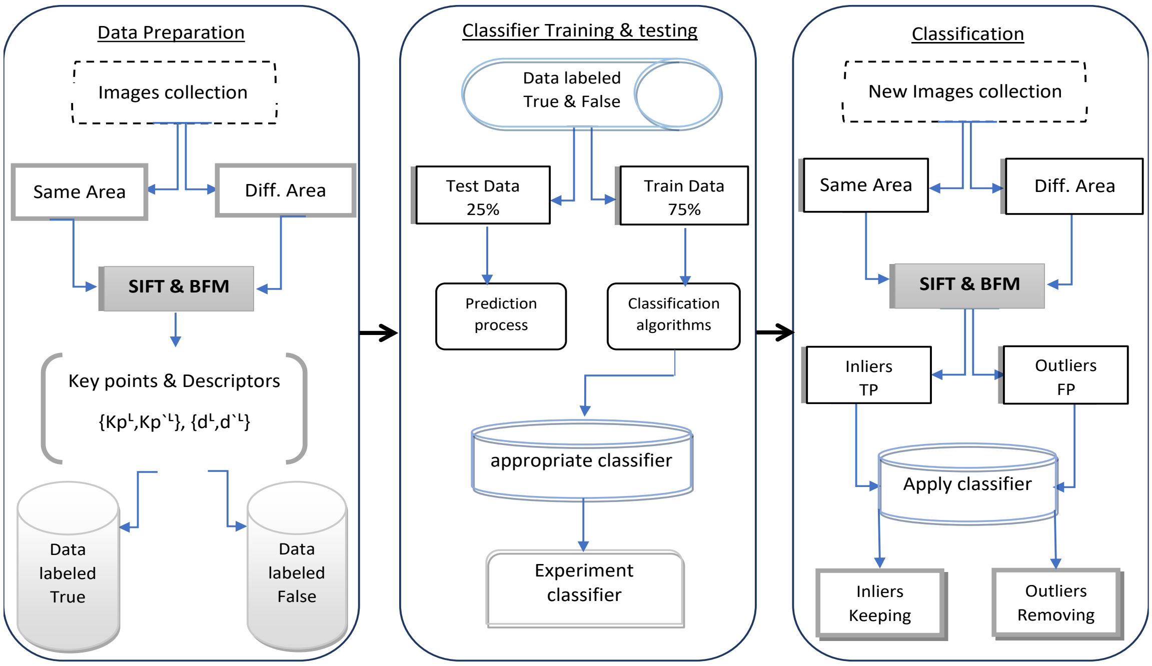


Figure 5. Diagram of proposed classifier outlier removal approach

4.3.2. Area under receiver operating characteristic

The AUROC is a popular performance metric [19] for evaluating the classification models. It informs us whether our model can correctly rank. For instance, in our binary classification model ("1" vs. "0"), the AUROC (see Figure 6) provides us the probability that the "1" image selected at random will have a higher prediction of being "1" compared with the randomly selected "0" image, and the interpretation of the work in AUROC gives us an example of a receiver operating characteristic curve. The worst degree is 0.5, whereas the best degree is 1.0 [20].

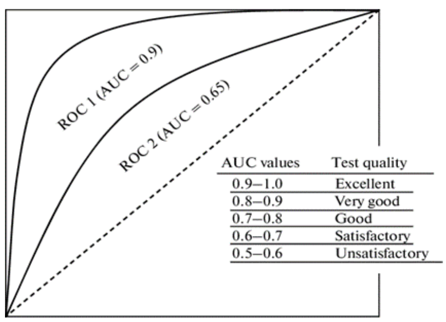


Figure 6. AUROC interpretation

4.3.3. Classification report

In machine learning models, the classification report can be used to evaluate the model performance. To learn more about the classification report the most important metrics are mentioned as follows:

- Precision: the classifier's ability not to label the descriptor positive that it is negative. In each class, it can be defined as the ratio of the TPs divided by the summation of TPs and FPs, as shown in (3):

$$Precision = \frac{TP}{(TP+FP)} \tag{3}$$

- Recall: the classifier's ability to find all positive descriptors. In each class, it can be defined as the ratio of the TPs divided on the summation of TPs and FNs, as shown in (4):

$$Recall = \frac{TP}{(TP+FN)} \tag{4}$$

- F1-score: the weighted harmonic means of both precision and recall, which is 1.0 for the best score and 0.0 for the worst score. The F1-score expression is given in (5):

$$f1 - score = \frac{2 \times (Recall \times Precision)}{(Recall + Precision)} \tag{5}$$

- Support: the number of actual iterations for each class in the dataset. It does not correspond to the differential among models but rather shows the process of performance evaluation.

4.3.4. Accuracy score

Accuracy score is one of the metrics used to evaluate classification models. In machine learning, the accuracy score is known as the best method to validate the models used in the classification problems. Formally, the accuracy has expression as in (6):

$$Accuracy = \frac{(TP+TN)}{(TP+FP+TN+FN)} \tag{6}$$

The accuracy result informs us the percentage of the accurate predictions. As shown in (6), it can compute the accuracy by dividing the number of correct predictions by the total number of predictions.

$$Accuracy = \frac{Number\ of\ correct\ Predictions}{Total\ number\ of\ Predictions} \tag{7}$$

5. COMPARISION TECHNIQUES AND ANALYSIS

For our model to be solid and effective, we need to verify this purpose by comparing the results with several well-known classification algorithms. Hence, we will give a brief overview of these algorithms as shown as follows:

5.1. Classification algorithms

In machine learning, many algorithms are widely used to find solutions to the problems of classification, regression, and clustering. In applying an appropriate algorithm of machine learning, it is supposed to select an available technique in supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning depending on the categories and types of data training [21].

5.1.1. Naïve Bayes

Naïve Bayes (NB) is a probabilistic model updated using training data, relying on conditional independence assumptions. Its advantages for its simplicity, good performance, suitability for small datasets, handling of binary and multiclass problems, and linear scales with few predictors. However, its overly simplistic, struggles, with continuous variables, requires data retention, isn’t deal for many classes, and can be computationally demanding with many variables [21].

5.1.2. Decision tree

A decision tree (DT) is used in classification and regression tasks, continually splitting data based on a specific parameter. It divides data into nods. Advantages include ease of use, flexibility with quantitative and categorical data, ability to handle missing values, and applicability to library book prediction and tumor diagnosis. Disadvantage include instability, limited control over tree size, sensitivity to sampling errors, local rather than global optimization, overfitting issues, and the potential solution of using RF via ensemble methods [21].

5.1.3. Gradient boosting

It’s a powerful machine learning algorithm that has a successfully considered in the wide space of applications that used in classification and regression problems. Gradient boosting (GB) is also known as the model of statistical prediction. The three steps involved in the algorithm are loss function, weak learner, and additive model [22]. The advantages are accurate results, fast training with a large dataset, and can handle categorical feature support. The disadvantages are it is prone to overfitting, expensive as it takes a long time to compute [23].

5.1.4. Random forest

RF combines multiple DT to tackle classification and regression problems, forming an ensemble approach. In Hos 1995 proposal, RF achieves high accuracy without overfitting by utilizing DTs with distinct oblique hyper-planes [24]. The advantages are: uses bagging and ensemble learning, reduces overfitting and variance by building multiple trees on data subsets, handles various variable types, copes with missing values, doesn't need feature scaling, efficient for non-linear parameters, robust to outliers, and noise-insensitive [25].

5.1.5. Logistic regression

It's also used for classification problems, yielding binary outcomes based on input variable values, such as spam email classification or tumor benignity prediction. Logistic regression (LR) offers advantages like simplicity, efficient computation, ease of training, compatibility with regularization, no need for input feature scaling, scalability to industrial problems, and robustness to data noise. However, LR has limitations, it doesn't handle nonlinear problems, is prone to overfitting. LR finds applications in risk disease prediction [21].

5.2. Model comparison

The proposed method is measured by computing the accuracy score and AUROC for a set of classification algorithms. To evaluate the proposal to be stronger, we selected five classification algorithms: NB, DT, GB, RF, and LR. In Table 1, the comparison values are provided. Table 2 shows the accuracy and AUROC score comparison among algorithms. RF is more accurate than the others. Figure 7 shown a visual comparison of the results.

Table 1. Comparison of the precision, re-call, and F1-score value of five classification

Classification algorithm	Dataset records		Precision (%)		Recall (%)		F1-score (%)	
	True (1)	False (0)	True (1)	False (0)	True (1)	False (0)	True (1)	False (0)
NB [21]	560K	560K	0.55	0.55	0.56	0.54	0.56	0.55
DT [21]	560K	560K	0.55	0.58	0.67	0.46	0.60	0.51
GB [22]	560K	560K	0.59	0.61	0.65	0.54	0.61	0.57
RF [24]	560K	560K	0.69	0.75	0.78	0.65	0.73	0.70
LR [21]	560K	560K	0.55	0.55	0.56	0.54	0.56	0.55

Table 2. Accuracy and AUROC comparison of five classification algorithms

Classification algorithm	Dataset records		Support		Accuracy	AUROC
	True (1)	False (0)	True (1)	False (0)		
NB	560K	560K	279838	280162	0.55	0.575311
DT	560K	560K	279838	280162	0.56	0.580730
GB	560K	560K	279838	280162	0.59	0.629364
RF	560K	560K	280062	279938	0.72	0.765546
LR	560K	560K	280062	279938	0.56	0.588984

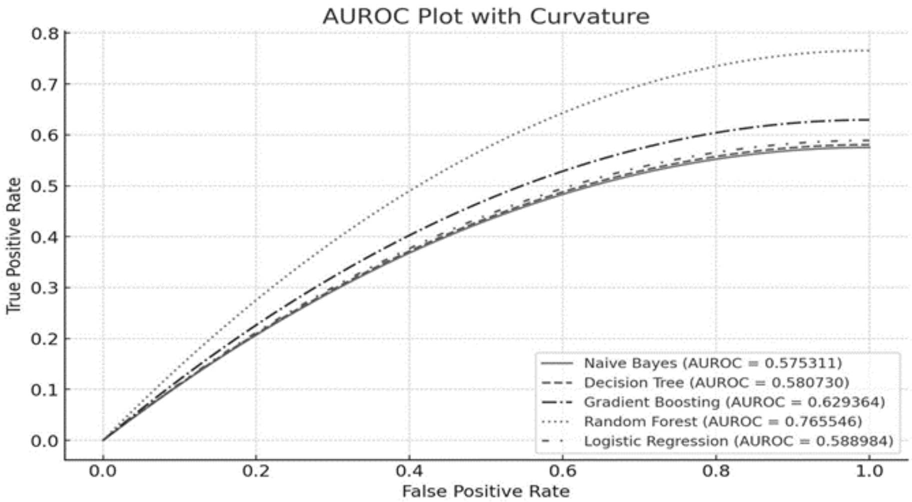


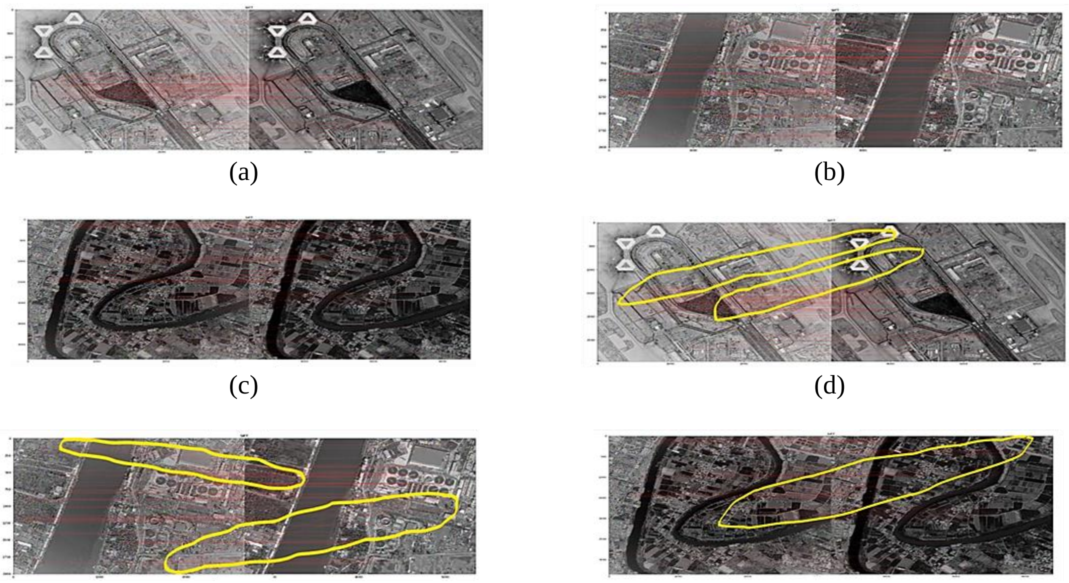
Figure 7. AUROC for five classification algorithms

6. EXPERIMENT MODEL AND RESULTS

Firstly, we used three different types of datasets, each type contains a few images, whether it is a single image or a bundle of images. The first dataset shown in Figure 8, which uses two images for a single geographical area (Figures 8(a)-(c)) with few differences in colors and size, has more details pertaining to the results compared with that shown in Table 3, about the application of the SIFT technique. Clearly, most of the points are correctly matched by BFM, while there are incorrectly matched descriptors (Figures 8(d)-(f)). To clarify the results obtained of three pairs of images and relying on the below table, we can infer the following points: the numbers of inliers (TP) are 36072, 20859, and 55825, and the computational accuracies are 80%, 88%, and 82%, respectively. The performance of the proposed new classifier involves the removal of outliers (−9018, −2844, and −12254) by applying in (9). The second dataset contains one pair image acquired in different geographical areas, as shown in Figure 9. Obviously, and because of the wrong matching of BFM, many incorrect descriptors are appeared. If we check the results in Table 3, then we can see that the accuracy is extremely low (04%). The new classifier was able to remove most of the outliers, which are approximately −4945.92. The third dataset as shown in Figure 10 includes the original single image, the accuracy is 93%, and the number of removed outliers is 396.2.

$$TP = accuracy \times N(r) \tag{8}$$

$$FP = accuracy \times N(r) - support(1) \tag{9}$$



(a) (b) (c) (d) (e) (f)

Figure 8. Visual matching process (a) Single geographical area, (b) Single geographical area, (c) Single geographical area, (d) Incorrectly matched, (e) Incorrectly matched, and (f) Incorrectly matched

Table 3. Result based on three data sets

Input images	Size	Support True	Support False	Classifier accuracy (%)	Inliers (TP)	Outliers (FP)
Three image pairs for same area with different colors and size						
Baghdad1	2.60 MB	45090	0	0.80	36072	-9018
Baghdad1_1	3.73 MB	45090				
Baghdad2	3.24 MB	23704	0	0.88	20859	-2844
Baghdad2_2	174 KB	23704				
Baghdad3	2.86 MB	68080	0	0.82	55825	-12254
Baghdad3_3	4.65 KB	68080				
One image pair for different area						
Bgd_23	293 KB	0	5152, 5152	0.04	206.08	-4945.92
Baghdad4	2.09 KB	0				
One exactly image pair for same area						
Baghdad5	261 KB	5660	0	0.93	5263.8	-396.2
Baghdad5	261 KB	5660				

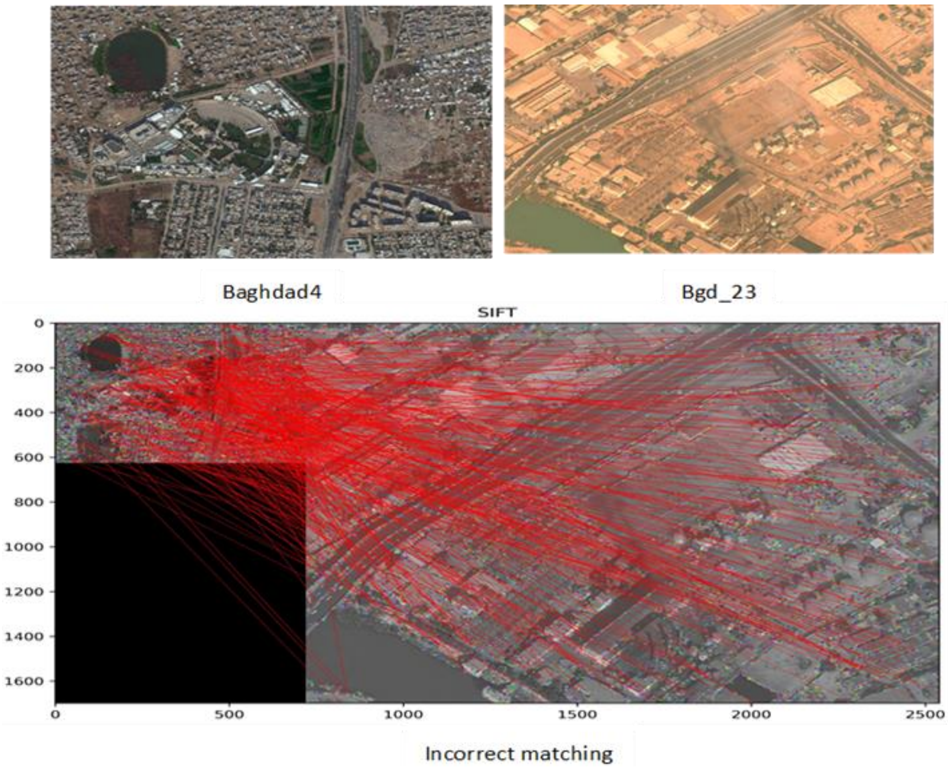


Figure 9. Two different images and incorrect matching

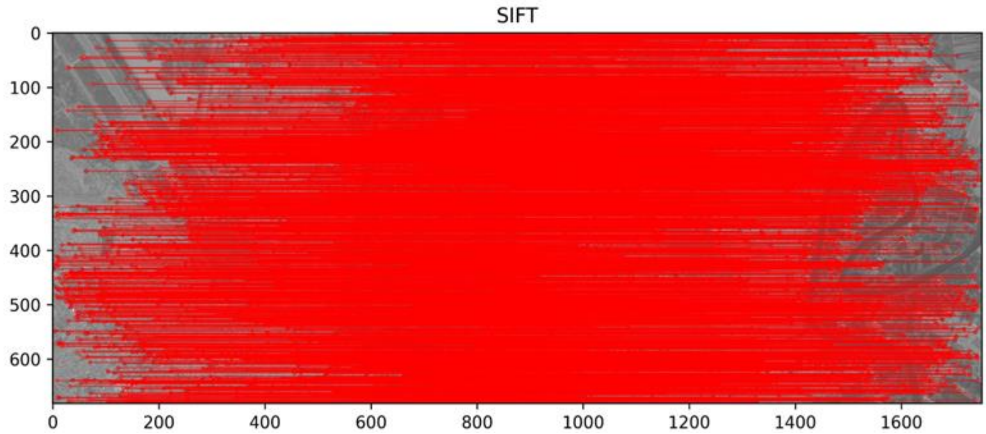


Figure 10. Perfect correct matching

Secondly, the experiment was intended to validate our new classifier, so we collected and prepared a new dataset for this issue. Figure 11 shows 20 different new images that are combined in the same way of combining the trained first dataset. We divided these images into two groups, the first one is prepared for the true dataset label, and the second one is prepared for the false dataset label. The first true dataset contained 58409 records, whereas the false dataset included 20214 records. Thus, the new dataset for validation in our new classifier consisted of 78623 records were given to SIFT and BFM for extracting the key-points and matching the descriptors, respectively. The accuracy scores directly applied over the new dataset was 66%, as illustrated in Table 4. In the same manner, we used in (8) and (9) to compute the number of inliers and outliers. The results of our validation shown in Table 5 verify the efficiency of our new classifier to remove the outliers. The number of kept inliers is 103782.36 records among the 116818 true records, whereas the number of removed outliers is −13035.64 records.

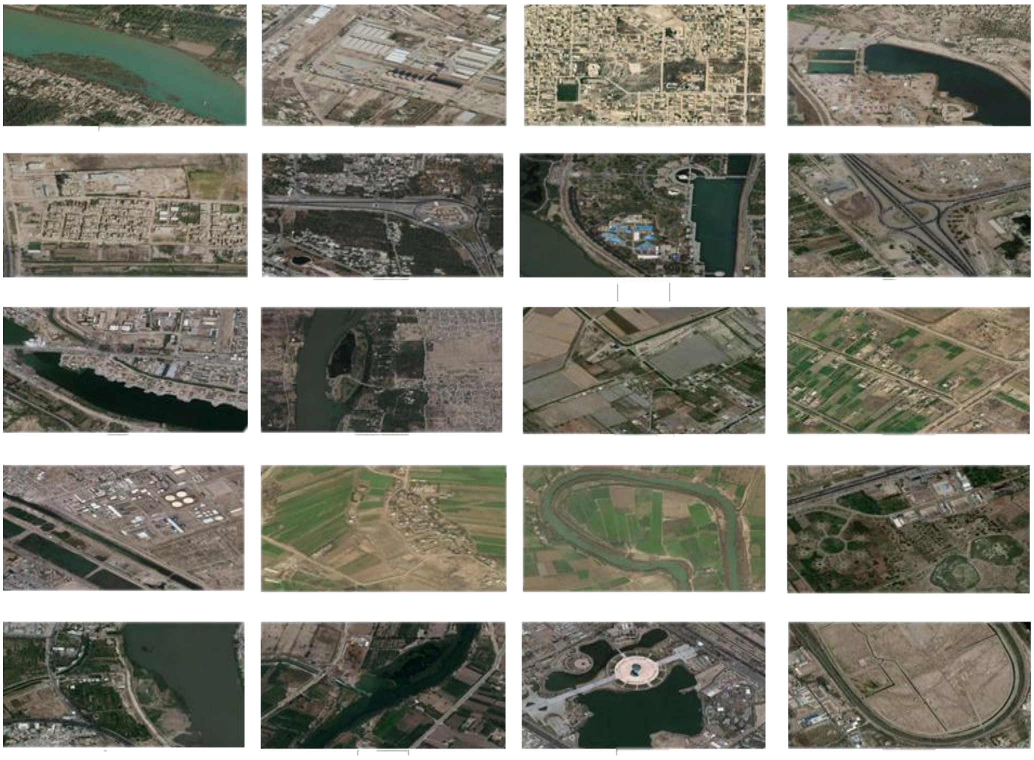


Figure 11. Validation images

Table 4. Validation dataset results

Classification algorithm	Dataset records		Precision		Re-call		F1-score		Accuracy
	True (1)	False (0)	True (1)	False (0)	True (1)	False (0)	True (1)	False (0)	
RF	116818	40428	0.75	0.27	0.82	0.20	0.78	0.23	0.66

Table 5. TPs and FPs by RF

Classification algorithm	Dataset records		New classifier accuracy (%)	Inliers (TP)	Outliers (FP)
	True	False			
RF	116818	40428	0.66	103782.36	-13035.64

7. CONCLUSION

This study suggested an adaptive approach for removing the outliers in the feature points based on image registration. First, we used SIFT to extract the key-points and descriptors from two images that were acquired in the same and different areas. The BFM approach is used to match the descriptors of images. A new binary classifier adaptive proves the effectiveness of a second filter for removing or reducing the outliers in the collected data. Experimental results have demonstrated the efficiency of the proposed approach. Finally, a comparison process among the classification algorithms is provided, and the evaluation of our method on the challenging dataset is performed. The RF algorithm can outperform other classification algorithms based on the computed accuracy score and AUROC, which are good for model performance.

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