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Detection of Objects in Satellite images using Supervised and Unsupervised Learning Methods

Chaitanya Malladi

Faculty of Computing
Blekinge Institute of Technology
SE-371 79 Karlskrona Sweden

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Contact Information:
Author(s):
Chaitanya Malladi
E-mail: chma15@student.bth.se

University advisor:
Dr. Huseyin Kusetogullari
Department of Computer Science

Faculty of Computing
Blekinge Institute of Technology
SE-371 79 Karlskrona, Sweden

Internet : www.bth.se
Phone : +46 455 38 50 00
Fax : +46 455 38 50 57

ABSTRACT

Context. Image processing on satellite imagery is an important challenge. In this area, the identification of objects in a satellite image is a pivotal task. Machine learning methods can be employed for this purpose as there has been significant amount of research in the area of image processing through machine learning. There are a large number of supervised and unsupervised algorithms based on machine learning which can perform image processing tasks.

Objectives. This study focused on evaluation of machine learning based object recognition algorithms on satellite images. The objectives were to identify one supervised and one unsupervised algorithm that were then to be implemented and compared over a generated dataset.

Methods. Literature review was conducted to identify the suitable algorithms for object recognition. Based on the literature survey, support vector machines and k-means were selected for supervised and unsupervised learning respectively. An experiment was performed to implement these algorithms. For the purpose of the experiment, a dataset consisting of objects from satellite images was created. The results of the experiment were evaluated using confusion matrix analysis and silhouette score analysis.

Results. The analysis of confusion matrix and silhouette score suggested that the support vector machine classification performed well unlike k-means which produced a weak cluster. The support vector machine was found to have an accuracy of 99.3%. On the other hand, the k-means clustering generated a silhouette score of 0.3237.

Conclusions. From the results of the research, it can be concluded that the support vector machine is found to be more applicable for object recognition on satellite images in comparison to k-means clustering.

Keywords: object recognition, satellite images, support vector machines, k-means clustering

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CONTENTS

LIST OF TABLES

LIST OF FIGURES

1 INTRODUCTION

Image processing is a major field in machine learning. Object recognition is a significant challenge in this domain [1]. Applications of object recognition can be found in the areas of automated navigation, object tracking, video surveillance [2]. This is a bigger challenge when complex images are considered [2]. It has been observed experimentally that the classical image processing algorithms fail when used on intricate natural images like satellite images [3]. At the same time, there is also an abundance of satellite imagery [4]. In addition, the capturing of remote sensor images is not restricted by weather, time, environmental issues [5]. This indicates that a large number of remote sensor images can be produced as per need. It is therefore essential to understand how efficient object recognition can be performed on them by the application of machine learning techniques.

1.1 Significance of object recognition in satellite images

Satellite images hold a large amount of data. Applications like environmental monitoring, spatial planning, natural resource management are among a few that have led to development of methods to extract remote sensor images [6]. There is also a trend of increase in the number and sophistication in the security applications, vehicle detection, and other urban applications that use remote sensor images [4], [6].

Object based image analysis meets the demand of handling large data within a limited time [6]. Object based classification reinforce the analysis performed on satellite images for perception of urban features [7]. This also finds applications in the areas of agriculture, land use, environmental monitoring, metrology [8].

As there is an abundance of available images, machine learning approaches can be applied. Object recognition in images achieves high recognition rate when machine learning techniques are used [9]. This is especially true in images which contain complex natural environment [10]. Satellite images can be considered under this classification of complex natural images.

1.2 Problem Statement

Machine learning is a broad area which encompasses various techniques. Each of these techniques is designed and applicable for specific tasks [11]. It remains to be identified what machine learning approach is best suited for object recognition in satellite images. Machine learning techniques can be classified into two categories, supervised learning and unsupervised learning [11]. There are several implementations under each of these.

Objects for which the features can be extracted from a satellite image are described as perceivable. Objects like flights, cars, buildings are perceivable [3]. The objects chosen for this study are: flights, and cars. To identify a suitable approach for identifying these objects in satellite images is the aim of this thesis.

1.3 Aim

The aim of this thesis is to identify supervised and unsupervised learning methods for object recognition in remotely sensed images. The algorithms will then be implemented and evaluated on a generated image sets of the two chosen perceivable objects, namely, flights and cars. Finally, based on the performance of the two approaches, analysis will be done to ascertain the approach that is more applicable.

1.3.1 Objectives

- Identify suitable supervised and unsupervised algorithms to perform the object identification
- Generate data sets corresponding to the objects to be identified, flights and cars
- Perform object recognition using the identified algorithms on a generated data set
- Evaluate the algorithms based on their performance in object recognition

1.4 Research Questions

RQ1: What are the supervised and unsupervised image processing methods suitable for object recognition?
To achieve the goals of this study, it is required to identify the supervised and unsupervised methods that are generally used. Among these, the image processing techniques that can be applied to object recognition are to be selected. The selected approaches have to be implemented as part of the experiment. RQ1 focusses on identifying and selecting the suitable methods.

RQ2: How do the methods chosen in RQ1 perform for object recognition on the generated data sets?
The methods selected in RQ1 are to be implemented. The performance of the algorithms is to be examined. For this, an image data set is to be generated. The methods are to be assessed on the data set. The evaluation of performance of the methods is the object of this research question.

RQ3: Which approach among the implemented methods has better performance for object recognition in satellite images?
The methods implemented are to be analyzed on the basis of their individual performance. The main aim of this study to identify the more suitable approach for object detection in satellite images is answered in this research question.

1.5 Outline

This report is organized in the following manner: Chapter 2 describes the background about object recognition in satellite images. The existing literature is discussed in this section. Chapter 3 presents the methods followed to achieve the objectives of this research. The results are presented and analyzed in Chapter 4. Chapter 5 contains the discussions based on the observed results, validity threats, and limitation of this study. The report is concluded in Chapter 6 with discussion on the potential future work that can be done to extend this research.

2 BACKGROUND

The background corresponding to the topics relevant to this study are discussed in this section.

2.1 Satellite Images

The aerial view of the surface of the earth can be captured from the sky using satellites. These images are useful for various purposes like urban planning, agriculture, weather monitoring, natural resource management. There are many providers online which provide satellite images.

Figure 2.1 Example satellite image

The figure above illustrates a typical satellite image of a city. This image is taken from an online source, ArcGIS, which provides high resolution satellite imagery [12]. These images hold lot of information in form of objects. Perceivable objects are those for which features can be evaluated [3]. The images in Figure 2.2 below are examples of perceivable objects that are taken from larger satellite images. Figure 2.2(i) and Figure 2.2(ii) are of cars taken from ArcGIS [12] whereas Figure 2.2(iii) and Figure 2.2(iv) are of augmented flights taken from FlightRadar24 [13].


(i)


(ii)


(iii)


(iv)

Figure 2.2 Example perceivable objects

For extraction of information from satellite images, the identification of such objects is necessary. It is the fundamental challenge in computer vision to identify objects in a scene [3]. Recognition consists of associating a label to an object based on its features [14].

2.2 Machine Learning

Earlier, remote sensed images were to be analyzed with the help of specialized equipment with the assistance of trained staff [14]. However, with the development of machine learning techniques, these tedious tasks can now be performed by computers with significantly lesser human support.

Machine learning consists of automated computing procedures which are designed to learn to solve a problem based on existing examples[15]. The learning may include gathering knowledge, understanding the knowledge, and to acquire a skill by experience [11], [16]. Such a method that implements learning would improve with more experience. It is applicable in scenarios where there is a large amount of data available for the learner [11].

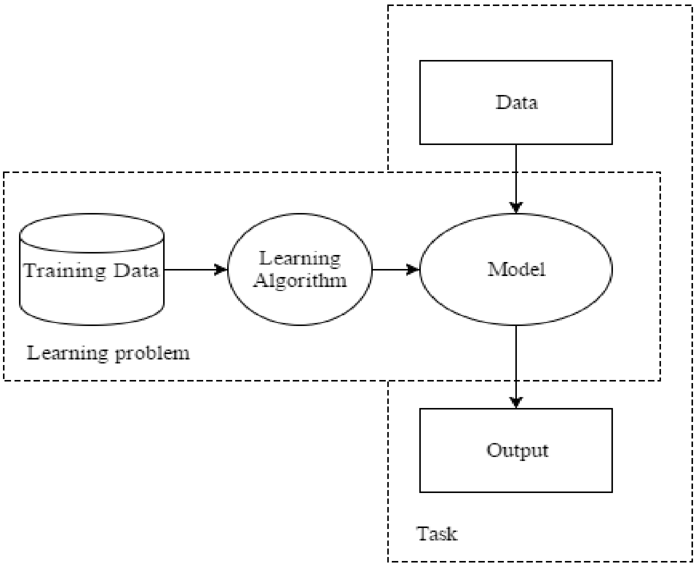

Figure 2.3 Machine Learning block diagram

Figure 2.3, adapted from [16], illustrates the basic structure of a machine learning solution. The learning algorithm employs methods to identify the relevant features of the training data to build a model. This is the learning task. Once the model is learnt, it can be employed to find the outcome for tasks [16].

2.2.1 Supervised Learning Methods

Under supervised learning, the machine learning model is built using training data which contains input and also the expected output. By the help of these, the model learns its functionality of providing an appropriate output when presented with an unseen input [11].

Supervised learning methods are commonly used to generate predictive models. Tasks like classification and regression are generally performed using supervised learning [16]

2.2.2 Unsupervised Learning Methods

Unsupervised learning involves the algorithm being presented with only the input data and a model is built to fit the observations. The input data are treated as random variables and patterns are identified among them to form groupings [11]. The model is not presented with the correct outputs expected from the inputs [17].

The generation of descriptive models is generally performed through unsupervised learning. Clustering, rule discovery, and matrix decomposition mainly use unsupervised methods [16].

It should however be noted that descriptive tasks can also be performed using supervised learning and predictive tasks can be done using unsupervised learning. Although, they are not the common applications [16].

2.3 Related Work

The literature relevant to the current study was studied to gain a better understanding of the current state of the field. The findings of this preliminary study are described in this section.

A fast and automatic approach to detect objects in images of large size is proposed in [9]. Experimentation was performed supported by calculations to show that the proposed technique provides faster recognition. A similar attempt was made in [3] to improve the accuracy of object detection in complex satellite images. The solution attempted to mimic the human vision system to improve the accuracy of detection.

Reference [4] used a GIS-based application to detect ships in high resolution satellite images. This is used for monitoring maritime activities. In [5], the task of identifying type of aircraft in satellite imagery was done with hierarchical recognition methods. By experimentally comparing different approaches, a superior method was recommended. The identification of vehicles in satellite images was performed in [18]. This was done using segmentation followed by classification. The usage of support vector machine for classification in satellite images was discussed in [19]. Experimentally it was shown that the algorithm can be faster and more accurate using active learning.

According to [20], in the place of satellite images, infra-red images were used and a sea-land segmentation algorithm was proposed. Grayness and texture of surface were studied to arrive at a Gray Smoothening Ratio as a feature descriptor around which an algorithm was developed to classify and segment the images into sea and land. In addition to this, the algorithm also had a function to fill and gaps that arise due to natural conditions such as fog or cloudy weather. In [21], the authors implemented a machine learning technique using Adaboost. The prime point of study in this paper, was to separate circular structures in satellite images. Adaboost, an ensemble of various machine learning classification algorithms to provide a superior classifier, and Haar, a series of statistical feature descriptors were primarily used to implement the tool. Adaboost was trained iteratively and Haar descriptors were directly implemented over the gray-level images so as to avoid segmentation. The final phases used a cascade of Adaboost classifiers so as to avoid re-detection at the various scales of the image. The end result is a separated set of images.

The study [22] focuses on retrieving images from high resolution satellite images using CNN based approaches. Multiple datasets were used with strong CNNs to observe strong improvement over existing approach. Reference [23] uses large set of image data to perform surface object recognition. Two methods based on CNN and SVM are proposed and compared. It is found that in the performed experiments, CNN had better performance. In [24], isolated airstrips are identified in satellite images using SVM after preprocessing the images. The algorithm performed very well providing an accuracy of 94%. It was able to identify airstrips among other common linear objects like roads, canals, and other objects.

3 METHODOLOGY

To perform a study, the applicable research methods are to be identified which can answer the research questions. A literature review followed by experimentation was deemed to be the suitable approach. Such a methodology can be classified as mixed as it employs both qualitative (in the form of literature review) and quantitative methods (in the form of experimentation) [25].

The research project methodology is depicted in Figure 3.1 below.

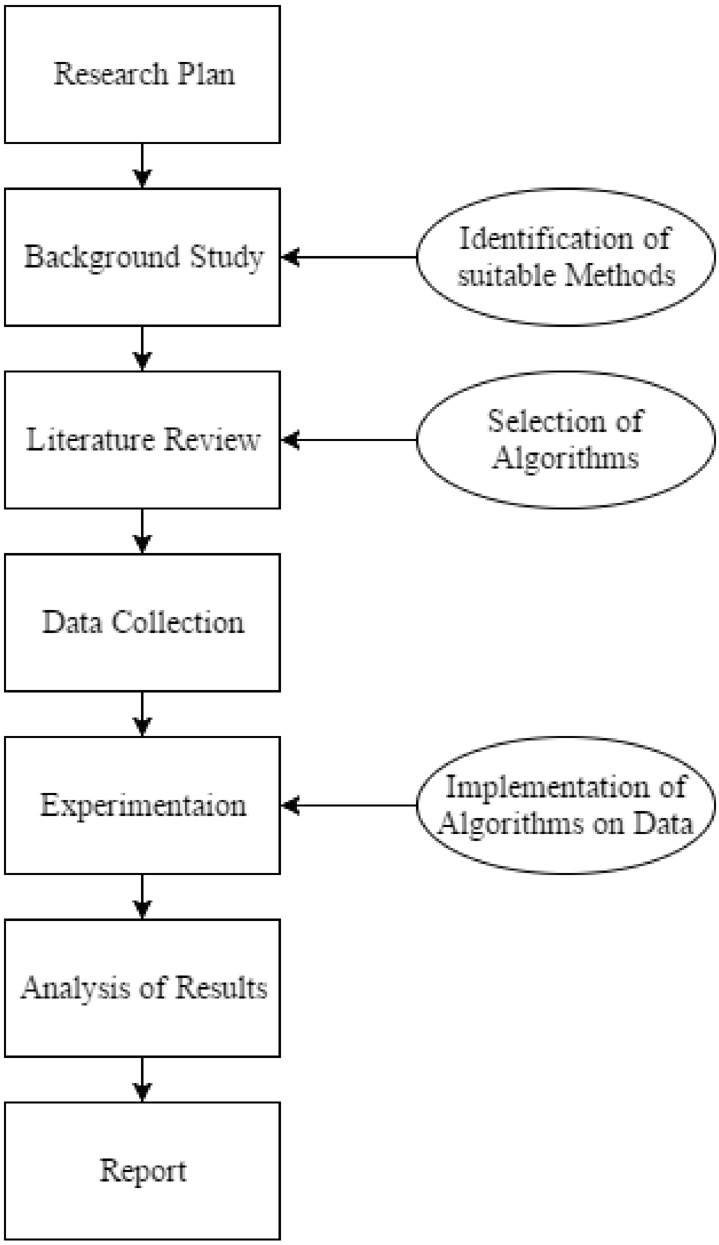

Figure 3.1 Research method

3.1 Literature Review

A literature review is the identification and examining of the existing research work in the chosen field to gain valuable information [26]. Literature review was performed to understand the existing learning algorithms and to choose the suitable supervised and unsupervised method for image classification. As the study was made to compare supervised and unsupervised algorithms, the literature review was performed to identify the most effective algorithm of each kind. The algorithms identified were further used in experimentation.

3.1.1 Supervised algorithms

Various supervised learning algorithms for object recognition were identified during background study. Of these, the most commonly used ones are listed below [27].

- **Support Vector Machines (SVM) –** Support vector machine is vector based method where the boundaries between the classes in a feature space are identified using the training data in order to perform classification [28].
- **Convolutional Neural Networks (CNN) –** Convolutional neural networks are feed forward networks which perform the pooling and convolution calculations alternatively for multiple times. They provide the classification as probability of each class [29].
- **Logistic Regression –** Logistic regression is a statistical method for binary classification that uses a sigmoid function. The coefficients for the function are generated from the training data.
- **k Nearest Neighbors (k-NN) –** k-Nearest neighbors is an instance based learning method where the classification is based on the closeness to the majority of the instances [30].

There have been multiple studies where the researchers investigated how several supervised algorithms performed in object recognition. Neural networks generate good models when there is large amount of data [29]. The current study is performed with a relatively smaller data set. Due to this, CNNs are not considered to be the right approach for this study. In [27], various supervised algorithms were evaluated on multiple performance measures. From this research, it was clear that the performance of logistic regression was poorer compared to other methods. Reference [31] focused on comparing k-NN and SVM on image classification. It was found that SVM outperformed k-NN by a slight margin. Based on these observations, Support Vector Machine was selected as the supervised learning algorithm to be implemented.

3.1.2 Unsupervised algorithms

Under unsupervised methods, the various unsupervised learning methods can be categorized into the following.

- **Clustering –** Clustering involves grouping the instances into subsets called 'clusters' based on the similarities they share [32], [33].
- **Anomaly detection –** Anomaly detection involves the identification of instances which do not fit into the patterns obtained from rest of the instances [34].

Anomaly detection was found to work well in applications where a large portion of the data has some similar qualities and few instances deviate from this. The deviating instances can be identified well using anomaly detection [34]. This method is not suitable to classify instances of roughly the same size. Clustering, on the other hand, partitions the data into regions based on similarities [35]. There exist several implementations of clustering. Several clustering methods were found in the literature which include K-means [36], branch and bound methods

[37], and graph based clustering methods [38]. K-means clustering was found to be the most widely used approach and is also effective in generating reliable clustering in most practical applications [33]. As a result of this literature review, it was determined to select k-means clustering as the unsupervised algorithm for experimentation.

Support vector machines and k-means clustering were chosen as the two algorithms for which the performance was to be evaluated. MATLAB implementations for these algorithms were used in the experiment. This study takes a first step to compare supervised and unsupervised algorithms and can be expanded to include other algorithms in the future.

3.2 Experiment

This section details the experimentation carried out for this study. This includes the data collection and the procedures of implementing the algorithms.

3.2.1 Data Collection

For the purpose of the experiment, it was required to have a labelled data set to test the algorithms on. The data set would have to consist of objects in remotely sensed images. These objects should be perceivable and be easily available on a satellite map since the data was to be collected manually. Additionally, the images of the objects are to be of a uniform scale and size for the object recognition to be performed. With these conditions, the objects that were chosen to be used were cars, and flights. The data set was generated manually by using online mapping websites ArcGIS [12] for cars and FlightRadar24 [13] for flights. ArcGIS [12] provides high resolution satellite imagery and hence images of cars were extracted from it and labelled as 'cars'. [13] contains satellite imagery augmented with flight images. These are only available in the form of graphically augmented images of flights. However, this is not considered to be a major issue as the background scene of a satellite image is preserved in these images. The goal is to perform object recognition in such a scene. It was pivotal to have the scene of the satellite image with perceivable objects in it and this was facilitated by the website. This was used to extract the flight objects and were labelled as 'flights'. One thousand objects of each category were captured. To maintain uniformity, both the object data sets generated consisted of images in the size of 32x32 pixels and in the PNG format. This format was used as no compression is the PNG format[39]. A summary of the data set generated is presented in Table 3.1.

Object	Number of instances	Size	Format	Source
cars	1000	32x32	PNG	ArcGIS [12]
flights	1000	32x32	PNG	FlightRadar24 [13]

Table 3.1 Data set summary

A few sample images from the data set are presented in Figure 3.2.

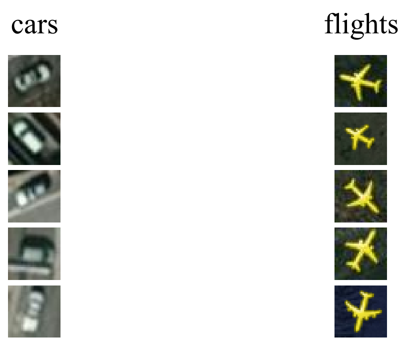

Figure 3.2 Sample images from the data set

3.2.2 Experimental Setup

An experiment was designed and performed to evaluate the performance of support vector machines and k-means clustering algorithms on the data set generated. The specifications of the experimental setup are described in this sub-section.

System Specifications:

The experiment was performed on a PC with the following configurations:

- CPU : Intel Core i5
- Processor type : 64-bit (x64)
- RAM : 8GB
- Operating System : Microsoft Windows 10
- Programming Environment : Matlab 2016b

Image processing depends on packages that are already available in softwares like Matlab[40]. Matlab provides toolboxes for image processing that make the tasks easier for users. The experiment was performed on the Matlab 2016b which was obtained under an academic license from BTH.

Dependent and Independent Variables:

- **Dependent Variables:** The experiment contains two dependent variables. First, the accuracy of the classification model, which indicates the correctness of the classifier. Second, the cluster validity measure of the clusters, which represents the quality of the cluster.

- **Independent Variables:** The classification algorithm based on support vector machines, the k-means clustering algorithm, and the image data set on which these algorithms are implemented are the independent variables.

Evaluation Metrics:

The implementation of support vector machines was used for classification. The classical method for evaluation of classification problems is using confusion matrix [41]. Further calculations can be made on the elements in the confusion matrix to identify accuracy, precision, sensitivity, and specificity [42]. Accuracy was chosen as the metric as the classes are of equal sizes and there is no possibility of class imbalance.

For the k-means clustering, the quality of the cluster is calculated using Silhouette score. The measurement of the quality of the cluster is done through evaluating the closeness of the samples in each of the generated clusters. Experimental studies have shown that silhouette score shows better performance with respect to evaluation of clusters [43].

3.2.3 Experimental Design

This section describes the procedure that was followed to implement the support vector machine algorithm and the k-means clustering algorithm.

Support vector machines:

The Matlab implementation of support vector machines was used for the experiment. The implementation was done using labelled data set which had their classes pre-defined for learning. The data for each class was split into 800 images for training and 200 images for testing. For each class, flights and cars, features were extracted from the training part using Bag-of-Features [44]. These features were used to generate a model using SVM. The model was tested on the test set consisting of 400 images (200 of each class). This process was repeated in a 5-fold cross validation method so that the entire data set would be used in the testing. This whole cross-validation process was repeated twice to ensure that the division would not generate biased training and testing data sets. The average confusion matrix for this was generated.

This process is illustrated in Figure 3.3.

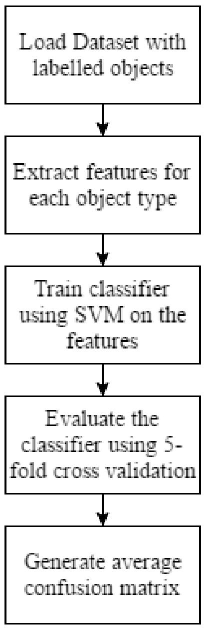

Figure 3.3 Support vector machine classification experiment

k-Means Clustering:

For unsupervised learning, the data doesn't need to be labelled. For this reason, the unclassified data set with 2000 images was used for clustering. For each image, a feature vector was generated using Scale Invariant Feature Transformation (SIFT) [45]. This set of feature vectors was clustered into two clusters using the k-means clustering algorithm. A Matlab implementation of this algorithm was used. Two clusters were chosen as it was known that the data set consists of two kinds of objects (cars and flights). The quality of the clusters was identified using Silhouette values of the generated cluster. The clustering process is repeated for 10 times to obtain the results.

Figure 3.4 presents the experimentation method corresponding to k-Means clustering.

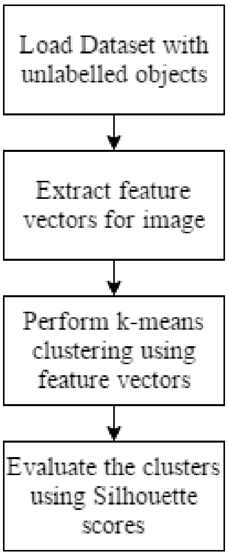

Figure 3.4 k-Means clustering experiment

4 RESULTS AND ANALYSIS

In order to answer the RQ1 a literature review was performed as described in Section 3.1. The suitable supervised and unsupervised learning methods were identified and presented in Section 3.1.

The answers for RQ2 and RQ3 are found in the results of the experiment conducted as described in Section 3.2. These results are presented and analyzed in this chapter.

4.1 Experiment Results

The experiment was performed in two parts where each of the algorithms was implemented. The results of each of the individual experiments are presented in this section.

4.1.1 Support vector machine classification

The object classification task was performed on the dataset with 2000 images and the model was evaluated using 5-fold cross validation performed two times.

The confusion matrices for each of the folds of this evaluation is presented in Table 4.1. This is followed by the average confusion matrix in Table 4.2

			Predicted	
Iterations	**Folds**	**Known**	**cars**	**flights**
Iteration 1	Fold 1	**cars**	99.50%	0.50%
		flights	1.00%	99.00%
	Fold 2	**cars**	99.30%	0.70%
		flights	0.60%	99.40%
	Fold 3	**cars**	99.50%	0.50%
		flights	1.00%	99.00%
	Fold 4	**cars**	99.00%	1.00%
		flights	0.50%	99.50%
	Fold 5	**cars**	99.60%	0.40%
		flights	0.80%	99.20%
Iteration 2	Fold 1	**cars**	99.70%	0.30%
		flights	0.60%	99.40%
	Fold 2	**cars**	99.10%	0.90%
		flights	1.00%	99.00%
	Fold 3	**cars**	99.30%	0.70%
		flights	0.80%	99.20%
	Fold 4	**cars**	99.20%	0.80%
		flights	0.50%	99.50%
	Fold 5	**cars**	99.60%	0.40%
		flights	1.00%	99.00%

Table 4.1 Confusion matrices for SVM classification

	Predicted	
Known	**cars**	**flights**
cars	99.38%	0.62%
flights	0.78%	99.22%

Table 4.2 Average confusion matrix

4.1.2 k-Means clustering

The clustering was evaluated using the silhouette score. The silhouette score indicates the cluster validity [43]. The clustering was performed for 10 iterations and the average silhouette score was computed. These results are presented in Table 4.3.

Iteration	Silhouette Value
Iteration 1	0.3241
Iteration 2	0.3234
Iteration 3	0.3243
Iteration 4	0.3234
Iteration 5	0.3235
Iteration 6	0.3240
Iteration 7	0.3235
Iteration 8	0.3242
Iteration 9	0.3233
Iteration 10	0.3235

Table 4.3 Silhouette Values for k-means clustering

4.2 Analysis

The assessment of results is equally important to the collection of results [46]. This section deals with the analysis of the results obtained in Section 4.1.

4.2.1 Support vector machine classification

From the confusion matrices in Table 4.1, accuracies of the classifier for the five folds in each iteration were calculated using Equation 1. As there is no class imbalance, the accuracy values provide a good evaluation of the classification. These are presented in Table 4.4.

$$Accuracy = \frac{True\ Positive + True\ Negative}{Total\ Observations}$$

Equation 1: Calculation of accuracy from confusion matrix

Iteration	Folds	Accuracy
Iteration 1	Fold 1	99.25%
	Fold 2	99.35%
	Fold 3	99.25%
	Fold 4	99.25%
	Fold 5	99.40%
Iteration 2	Fold 1	99.55%
	Fold 2	99.05%
	Fold 3	99.25%
	Fold 4	99.35%
	Fold 5	99.30%

Table 4.4 Accuracies for each fold of SVM classification

The average accuracy of the SVM classifier was calculated as 99.3%. The standard deviation for the values is 0.12 which indicates low dispersion in the observed results. This indicates that the generated classifier is very accurate.

4.2.2 k-Means clustering

The average silhouette score for the clustering algorithm was found by performing the mean of the silhouette scores of each iteration in Table 4.3. The average silhouette value was calculated as 0.3237. The standard deviation for these was found to be 0.0003.

The silhouette value for a cluster ranges from -1 to +1. A higher value represents a better cluster. The quality of the cluster can be judged using the silhouette score based on the guidelines defined in Table 4.5. These criteria were defined in [47].

Silhouette score range	Cluster quality
0.71 to 1.00	Strong structure
0.51 to 0.70	Reasonable structure
0.26 to 0.50	Weak structure
Less than 0.26	No substantial structure

Table 4.5 Cluster quality based on silhouette score

The k-means cluster implemented has a silhouette score of 0.3237. This indicates that the clusters formed are belonging to a weak structure.

4.2.3 Normalization of results

The results obtained for the two methods belong to different scales. For performing comparison, they were normalized to a common scale of 0 to 100 using Equation 2. The normalized values are presented in Table 4.6.

$$Normalized\ Value = \frac{Observed\ Value - Range\ Minimum}{Range\ Maximum - Range\ Minimum}$$

Equation 2 Normalization of results

Algorithm	Observed Value	Range Minimum	Range Maximum	Normalized Value
SVM Classifier	99.30	0	100	**99.30**
k-Means Clustering	0.3237	-1	1	**66.18**

Table 4.6 Normalized results

The normalized values were found to be 99.30 for the supervised SVM classifier and 66.18 for the unsupervised k-means clustering.

5 DISCUSSIONS

This part of the report consists of discussions regarding the findings of the experiment. The threats to the validity of this research and its limitations are detailed in this section. Along with these, the answers to the research questions are also summarized.

Object recognition is a major challenge in the evolving field of image processing. It finds applications in various areas including satellite imagery. The algorithms of object recognition that exist can be extended to satellite images. However, it remained to be identified how supervised approaches and unsupervised approaches perform relatively for this task. The current study was performed to identify this.

Through studying the existing literature, several algorithms were identified. Of these, support vector machines and k-means classification were selected as part of this study. The experiment was performed using the Matlab implementations of these algorithms.

The analysis of the results of the experiment indicate that the classification by support vector machine gives highly accurate results. On the other hand, the k-means clustering approach generated a weak cluster implying that the clustered data wouldn't have high closeness among the elements in each cluster. The SVM was evaluated with accuracy and k-means with silhouette score. The best measure for each of the algorithms was identified individually as a common metric for comparison is not available. The chosen evaluation measures provide a good representation of the performance of the algorithms. Furthermore, the obtained results are normalized to a common scale to facilitate comparison of the algorithms. These observations indicate that support vector machines perform better for object identification in satellite images when compared to k-means clustering. This is confirmed by the accuracies and silhouette scores along with the normalized values which show that SVM classifier has higher value compared to k-means clustering. The accuracy and silhouette score are also observed to have low spread based on the standard deviation values.

This provides us with the knowledge that SVM has an edge over k-means clustering when object recognition in satellite images is considered. This study can be extended to other algorithms to comprehensively identify how they perform against each other.

5.1 Threats to validity

The threats to the validity of the study were mitigated by performing the research in a methodical manner. The following mitigation steps were taken.

Internal validity:

Internal validity may be affected when the literature review or the experimentation are performed incorrectly.

- The algorithms were chosen after careful literature review based on their performance described in existing studies. The algorithms that were deemed to be better suited for object recognition in satellite images were selected.
- The experiment for classification was performed and evaluated using 5-fold cross validation to ensure that all the images are used for testing in one of the iterations. This was repeated two times so as to avoid favorable division that might have happened.
- The clustering was repeated 10 times and the mean of the silhouette score was taken as the observed result.

External validity:

The data set was generated for two object types from two sources. The research may not be applicable when generalized to other object types. This was addressed by choosing general feature selection approaches which weren't specific to the object types.

5.2 Limitations

This study is constrained in the following ways.

- The scope of this study was limited to identifying and evaluating only two algorithms. The observations from the results of these two algorithms were used to generate the conclusions.
- The metrics of the algorithms are not directly comparable. This is addressed to some extent by normalizing the values to represent a common scale.
- The experiments were performed using general feature selection methods. There are existing approaches designed specifically for particular object types. These were not considered because the focus of this study was to evaluate the algorithms for general object recognition.
- The data collection was performed manually. This might create a biased data set which consists of only the objects which are easily identifiable to the eye and not the instances of objects which might be complex to identify.

5.3 Answers to Research Questions

RQ1: What are the supervised and unsupervised image processing methods suitable for object recognition?
Answer: By performing a literature review, it was found that there exist several supervised and unsupervised object recognition methods. By interpreting previous studies, among these, one supervised algorithm and one unsupervised algorithm were selected based on performance. This selection resulted in the choice of Support Vector Machine (SVM) as the supervised algorithm and k-means clustering as the unsupervised algorithm.

RQ2: How do the methods chosen in RQ1 perform for object recognition on the generated data sets?
Answer: The algorithms were used to perform object recognition on a generated data set. The performance of the algorithms was evaluated. The support vector machine algorithm had an accuracy of 99.3%. The k-means clustering was found to have a silhouette value of 0.3237. The normalized results were calculated as 99.3 and 66.18 for SVM and k-means algorithms respectively.

RQ3: Which approach among the implemented methods has better performance for object recognition in satellite images?
Answer: The analysis of the observed results indicates that the support vector machines are better suited for object recognition in remotely sensed images in comparison to k-means clustering. The evaluation performed on these algorithms conclusively illustrates this through the accuracy and silhouette values respectively.

6 CONCLUSION AND FUTURE WORK

6.1 Conclusion

Satellite imagery hold a large amount of information. However, to use this information, it needs to be extracted from the raw image data. Object recognition is a method that can help the extraction of information from satellite images. Two object recognition approaches, one supervised and one unsupervised, were chosen based on their performance observed in earlier studies. These algorithms were then evaluated on satellite images as a part of this study. Support vector machines and k-means clusters were used on a two-object data set to evaluate their performances and identify the approach which is comparatively better. Using the normalized values, it was found that k-means clustering performed poorly in comparison to support vector machine.

From these results, a conclusion can be drawn that the supervised approach of support vector machines is more applicable for use in object recognition on satellite images than the unsupervised k-means clustering.

6.2 Future work

This study can be further enhanced by implementing and evaluating more object recognition algorithms to identify their performance. Also, it can be explored in future research how the results are affected if the feature selection is done based on the objects in the database.

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