LOVELY PROFESSIONAL UNIVERSITY

Transforming Education Transforming India

Object Detection in Satellite Imagery

S.NO	Registration Number	Name of the Student	ROLL No
1.	**12224006**	Yashwanth Booram	68

Submitted to: **Dr. Dimple Nagpal**, (28531)
Lovely Professional University
Jalandhar, Punjab, India

ABSTRACT

Context. Processing images from satellite photography presents a significant difficulty. Finding things in a satellite image is a crucial task in this field. As a great deal of study has been done in the field of machine learning image processing, machine learning techniques can be used for this. Image processing tasks can be carried out via a multitude of machine learning-based supervised and unsupervised techniques.

Goal. This study evaluated object recognition systems based on machine learning using satellite photos. The goals were to choose one supervised and one unsupervised method, which would thereafter be put into practice and contrasted using a dataset that was created.

Techniques. A review of the literature was done to determine the best algorithms for object recognition. Support vector machines and k-means were chosen for supervised and unsupervised learning, respectively, based on the literature review. To put these algorithms into practice, an experiment was conducted. A dataset of objects from satellite pictures was produced specifically for the project. Both silhouette score analysis and confusion matrix analysis were used to assess the experiment's outcomes.

Results. In contrast to k-means, which resulted in a weak cluster, the support vector machine classification worked well, according to the examination of the confusion matrix and silhouette score. It was discovered that the accuracy of the support vector machine was 99.3%. The k-means clustering, on the other hand, produced a silhouette score of 0.3237.

Conclusions. The study's findings indicate that, when it comes to object recognition on satellite photos, support vector machines are more useful than k-means clustering.

Keywords: object recognition, satellite images, support vector machines, k-means clustering, Classification; Satellite Imagery.

CONTENTS

LIST OF TABLES

List of Figures

1. INTRODUCTION

One of the main areas of machine learning is image processing. In this arena, object recognition is a major challenge [1]. Video surveillance, object tracking, and automated navigation are some of the fields in which object recognition is used [2]. When complicated images are taken into account, this becomes more difficult [2]. Experimental research has shown that complex natural images, such as satellite photographs, are beyond the capabilities of the traditional image processing methods [3]. Simultaneously, a wealth of satellite imagery is available [4]. Furthermore, weather, time, or environmental constraints do not impede the capture of distant sensor images [5]. This suggests that several remote sensor images can be generated on demand. Therefore, it is crucial to comprehend how effectively machine learning techniques can be applied to them to conduct object detection.

1.1 Significance of object recognition in satellite images

Large amounts of data can be found in satellite photos. A number of applications, including natural resource management, spatial planning, and environmental monitoring, have prompted the development of techniques for extracting images from remote sensors [6]. Additionally, there is a tendency toward a growth in the quantity and sophistication of remote sensor image-based urban applications such as vehicle detection and security [4], [6].

The need to handle huge data in a constrained amount of time is satisfied by object-based image analysis [6]. The analysis carried out on satellite pictures to perceive urban features is reinforced by object-based classification [7]. Applications for this are also found in the fields of metrology, agriculture, land use, and environmental monitoring [8].

Machine learning techniques can be used because there are many photos available. When machine learning techniques are applied, object detection in photos gets a high recognition rate [9]. This is particularly true for pictures that feature intricate natural settings [10]. This classification of complex natural images includes satellite photographs.

1.2 Problem Statement

Machine learning is a large field that includes many different methods. Every one of these methods is intended to be used for a certain purpose [11]. Which machine learning technique is most appropriate for satellite picture object recognition is still up for debate. Supervised learning and unsupervised learning are the two categories into which machine learning approaches may be divided [11]. Each of these has a number of implementations.

Perceivable objects are those for which features can be retrieved from a satellite image. One can perceive things like automobiles, buildings, and flights [3]. The study's chosen objects are automobiles and airplanes. The purpose of this thesis is to establish an appropriate method for recognizing these items in satellite photos.

1.3 Aim

Finding supervised and unsupervised learning strategies for object detection in remotely sensed images is the goal of this thesis. After that, the algorithms will be put into practice and assessed using created image sets of the two selected perceivable objects, namely, aircraft and

automobiles. Ultimately, an analysis will be conducted to see which of the two methodologies performs better in order to determine which is more suitable.

1.3.1 *Goals*

- Determine appropriate supervised and unsupervised methods for identifying objects.
- Create data sets that correlate to the specified objects, such as vehicles and flights.
- Using the identified algorithms, identify objects on a created data set.
- Assess the algorithms according to how well they recognize objects.

1.4 Outline

The following is how this report is arranged: The background information on object recognition in satellite images is covered in Chapter 2. This section discusses the literature that is currently available. The techniques used in Chapter 3 to accomplish the goals of this study are presented. Chapter 4 presents and analyzes the findings. The discussions based on the study's limitations, validity threats, and observed results are found in Chapter 5. Chapter 6 of the report wraps up with a discussion of possible future research directions for this study.

2. BACKGROUND

This section discusses the background information related to the study's pertinent subjects.

2.1 Satellite Images

Satellites can be used to take pictures of the earth's surface from space. Numerous applications, including natural resource management, agribusiness, urban planning, and weather monitoring, can benefit from these photos. Satellite photos are available from numerous providers on the internet.

An example of a typical city satellite image is shown in the above graphic. This picture was obtained from ArcGIS, an online resource that offers high-resolution satellite imagery [12]. These photos, which include objects, contain a wealth of information. Objects that have evaluable qualities are considered perceivable [3]. Examples of observable items from bigger satellite photos are shown in Figure 2.2 below. Cars from ArcGIS [12] are shown in Figures 2.2(i) and 2.2(ii), while augmented flights from FlightRadar24 [13] are shown in Figures 2.2(iii) and 2.2(iv).

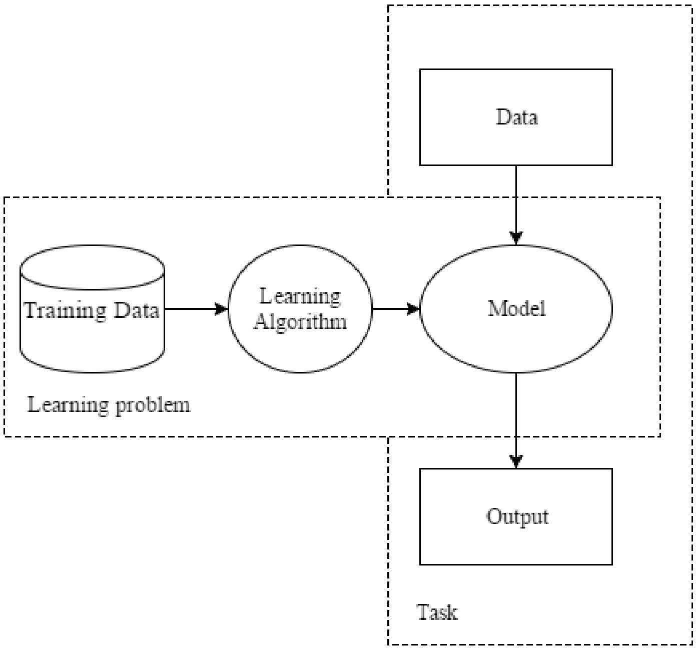
(i) (ii) (iii) (iv)

Such objects must be identified in order to retrieve information from satellite photos. Identifying items in a scene is the core problem of computer vision [3]. Assigning a label to an object based on its characteristics is the process of recognition [14].

2.2 Machine Learning

In the past, professional personnel and specialized equipment were required to evaluate remote sensing photos [14]. But thanks to advances in machine learning, computers can now complete these tiresome jobs with a great deal less assistance from humans.

Automated computer processes that are built to learn how to solve a problem based on prior examples make up machine learning [15]. Learning could involve acquiring information, comprehending that information, and developing a skill by practice [11], [16]. An approach that applies learning like this would get better with practice. It can be used in situations where the learner has access to a lot of data [11].



An example of a machine learning solution's fundamental structure is shown in Figure, which is taken from [16]. In order to create a model, the learning algorithm uses techniques to find the pertinent characteristics in the training set. This is the assignment for learning. The model can be used to determine task outcomes once it has been trained [16].

2.2.1 Supervised Learning Methods

In supervised learning, training data that includes both input and the desired result is used to build the machine learning model. These aid in the model's learning process so that it can produce a suitable output in the event of an unseen input [11]. Predictive models are often created via supervised learning techniques. supervised learning is often used to complete tasks like regression and classification [16].

2.2.2 Unsupervised Learning Methods

In unsupervised learning, an algorithm is given simply the input data and is tasked with creating a model that fits the observations. Groups are created by treating the incoming data as random variables and looking for patterns among them [11]. The right outputs that should be produced from the inputs are not provided to the model [17].

In general, unsupervised learning is used to generate descriptive models. Unsupervised techniques are typically used in matrix decomposition, rule discovery, and clustering [16]. It should be remembered, though, that supervised learning can also be used to complete descriptive tasks, while unsupervised learning can be used to complete prediction tasks. Nevertheless, they are not the typical uses [16].

2.3 Related Work

To better grasp the current state of the area, the literature pertinent to the topic was examined. This section describes the preliminary study's findings.

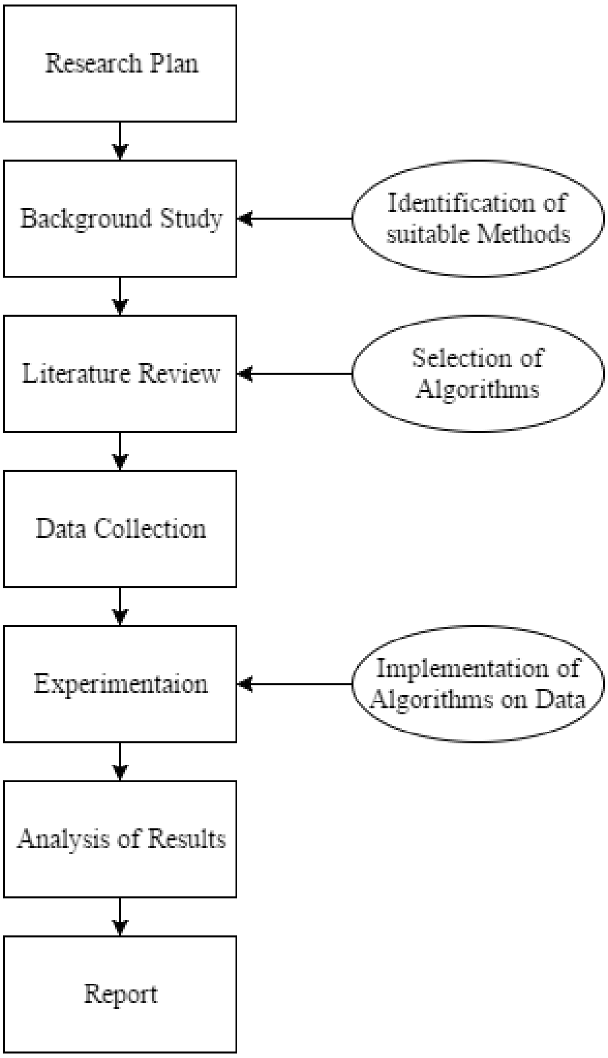
In [9], a quick and automatic method for identifying items in large-scale photos is suggested. Calculations and experimentation were used to demonstrate how quickly the suggested method can identify objects. A comparable endeavor to enhance the precision of object identification in intricate satellite photos was undertaken in [3]. In an effort to increase detection accuracy, the approach tried to imitate the human visual system.

A GIS-based program was utilized by Reference [4] to find ships in high-resolution satellite photos. This is employed to keep an eye on maritime activity. In [5], hierarchical recognition techniques were used to detect the kind of aircraft in satellite imagery. Through experimental comparison of various methodologies, a better solution was suggested. Vehicle recognition by satellite imagery was done in [18]. Segmentation and then classification were used to accomplish this. In [19], it was explored how support vector machines can be used to classify satellite photos. Active learning has been demonstrated to make the algorithm both faster and more accurate in experiments. Infrared images were employed in place of satellite images, and a sea-land segmentation technique was suggested, according to [20]. An algorithm was designed to identify and partition the photos into land and sea based on the Gray Smoothening Ratio, which was determined by analyzing the surface's texture and grayness. Furthermore, the system was designed to address any gaps that may come from environmental factors like fog or overcast weather. The authors used Adaboost to construct a machine learning approach in [11]. The primary goal of this paper's investigation was to identify circular buildings in satellite photos. The tool was mainly implemented using Adaboost, an ensemble of different machine learning classification methods to give a superior classifier, and Haar, a set of statistical feature descriptors. In order to prevent segmentation, Adaboost was trained iteratively and Haar descriptors were applied directly over the gray-level images. To prevent re-detection at different image scales, a cascade of Adaboost classifiers was employed in the last stages. An independent series of photos is the final output. The work [12] focuses on applying CNN-based techniques to retrieve images from high quality satellite photographs. Strong CNNs were applied to a number of datasets, demonstrating a significant improvement over the previous method. Reference [13] performs surface item recognition using a vast collection of picture data. Two CNN and SVM-based approaches are put forth and contrasted. It is discovered that CNN fared better in the trials that were conducted. After preprocessing the pictures, isolated airstrips are found in satellite images using SVM in [14]. The system delivered a 94% accuracy rate, which is quite good. Among other typical linear things like highways, canals, and other objects, it was able to recognize airstrips.

3. METHODOLOGY

Finding the appropriate research techniques that can address the research questions is the first step in conducting a study. It was decided that the best course of action would be to conduct a literature review and then experiment. A methodology like this can be categorized as mixed as it uses both quantitative (by experimental) and qualitative (via literature research) methodologies [20].

The technique for the research project is shown in Figure below.



3.1 Literature Review

Finding and analyzing the body of research that has already been done in a topic of interest in order to obtain important knowledge is called a literature review [16]. To comprehend the current learning algorithms and select the best supervised and unsupervised technique for picture classification, a survey of the literature was done. The literature review was done in order to determine which type of algorithm was the most effective, as the study was designed to compare supervised and unsupervised algorithms. Additional experiments were conducted using the indicated algorithms.

3.1.1 Supervised algorithms

Background research yielded a variety of supervised learning methods for object recognition. The ones that are most frequently used are mentioned below [17].

- **Support Vector Machines (SVM):** Using training data, SVM is a vector-based approach for performing classification that finds the boundaries between classes in a feature space [28].
- **Convolutional neural networks:** CNNs, are feed forward networks that repeatedly execute the pooling and convolution computations in an alternative manner. They give the probability of each class's classification [19].
- **Logistic Regression:** Using a sigmoid function, logistic regression is a statistical technique for binary classification. The training data is used to create the function's coefficients.
- **k-NN, or k-Nearest Neighbour's**, is an instance-based learning technique in which the majority of instances are classified based on proximity to one another [20].

Researchers have examined the performance of several supervised algorithms in object recognition in a number of studies. In situations where there is a lot of data, neural networks provide accurate models [19]. The present investigation is conducted using a comparatively smaller dataset. CNNs are therefore not thought to be the best method for this investigation. Several supervised algorithms were assessed using a variety of performance metrics in [17]. It was evident from this study that logistic regression performed worse than other techniques.
A comparison of k-NN and SVM for image classification was the main emphasis of reference [11]. SVM was discovered to perform marginally better than k-NN. Support Vector Machine was chosen as the supervised learning algorithm to be used in light of these findings.

3.1.2 Unsupervised algorithms

The different unsupervised learning techniques fall under the following categories under unsupervised methods.

- **Clustering:** In clustering, instances are grouped into "clusters" according to the similarities between them [12, 13].
- **Anomaly detection:** This process entails locating instances that deviate from the patterns seen in the remaining instances [14].

It has been discovered that anomaly detection functions best in situations where a sizable percentage of the data shares certain characteristics and just a small percentage deviates from them. Anomaly detection is a useful tool for identifying the outliers [14]. Classifying instances of approximately the same size is not appropriate for this strategy. In contrast, clustering divides the data into groups according to shared characteristics [15]. There are multiple clustering implementations available. Numerous clustering techniques, such as K-means [16], branch and bound techniques, were discovered in the literature. as well as graph-based clustering techniques [17, 18]. It was discovered that K-means clustering is the most popular method and that it produces dependable clustering in the majority of real-world applications [13]. This literature study led to the decision to choose k-means clustering as the unsupervised algorithm to be tested.

The two methods whose performances were to be assessed were support vector machines and k-means clustering. In the experiment, MATLAB implementations of these techniques were utilized. This work compares supervised and unsupervised algorithms in an initial phase and has the potential to be extended to different algorithms in the future.

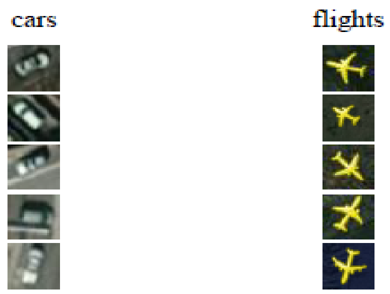
3.2 Experiment

The experiments conducted for this study are described in depth in this section. This covers the steps involved in gathering data and putting the algorithms into practice.

3.2.1 Data Collection

A labelled data set was necessary for the experiment's objectives in order to test the algorithms. It would be necessary for the data set to include items from remotely sensed photos. These were supposed to be observable and easily accessible on a satellite map, as the information was going to be gathered manually. In order to execute object recognition, the images of the items must also have a constant size and scale. Cars and airplanes were selected as the objects to be employed under these circumstances. The data set was created by hand using the online mapping services FlightRadar24 [13] for aircraft and ArcGIS [12] for automobiles. High quality satellite imagery is available through ArcGIS [12], from which pictures of cars were taken and classified as "cars." includes satellite imagery that has been enhanced with aerial photos [13]. Only visually enhanced photographs of flights are offered in this format. Since the backdrop scene of a satellite image is retained in these photographs, this isn't thought to be a big deal. The objective is to identify objects in a setting like this. Having the scene of the satellite image with observable items in it was crucial, and the website made this possible. The flight objects, which were designated as "flights," were extracted using this method. For every category, a thousand things were recorded. Both of the object data sets that were created included PNG-formatted, 32x32 pixel images in order to ensure consistency. Since the PNG format does not compress, this format was utilized[39]. Table 3.1 provides an overview of the generated data set.

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



3.2.2 Experimental Setup

The effectiveness of k-means clustering and support vector machines on the created data set was assessed through the design and execution of an experiment. This subsection describes the experimental setup's specifications.

System Specifications:

The following setups were used on the PC used for the experiment:

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

Software tools that are already included in programs like Matlab are necessary for image processing [20]. Matlab offers image processing toolboxes that simplify jobs for users. The Matlab 2016b, which was used for the experiment, was acquired from BTH under an academic license.

Dependent and Independent Variables:

- **Dependent variables:** There are two dependent variables in this experiment. First, the classifier's correctness is indicated by the classification model's accuracy. Second, the clusters' cluster validity measure, which indicates the cluster's level of quality.

- **Independent Variables:** These include the k-means clustering algorithm, the support vector machine-based classification algorithm, and the picture data set that these algorithms are applied to.

Evaluation Metrics:

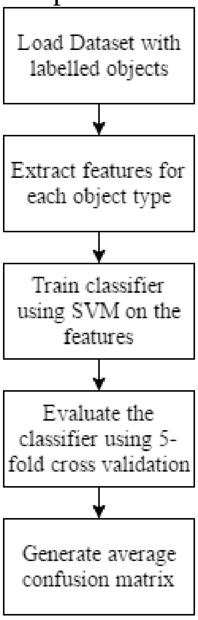
Support vector machines were employed in the categorization process. Confusion matrix analysis is the traditional method for evaluating classification issues [11]. Accuracy, precision, sensitivity, and specificity can be determined by doing further calculations on the components in the confusion matrix [12]. Since there is no chance of a class imbalance and the classes are all the same size, accuracy was selected as the metric.

The Silhouette score is used to determine the cluster's quality in k-means clustering. By measuring the proximity of the samples within each of the created clusters, the quality of the cluster is determined. Empirical research has demonstrated that the silhouette score performs better when evaluating clusters [13].

3.2.3 Experimental Design

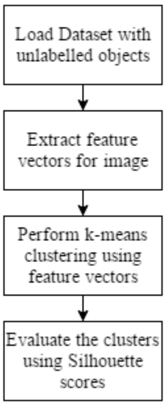
The process used to apply the k-means clustering algorithm and the support vector machine algorithm is explained in this section.

Support vector machines:
The experiment made use of the support vector machine implementation in Matlab. The labelled data set, with pre-defined learning classes, was used for the implementation. Each class's data was divided into 200 images for testing and 800 images for training. Using Bag-of-Features, features were extracted from the training section for each class, airplane, and automobile [44]. SVM was used to create a model based on these features. The 400 photos in the test set (200 for each class) were used to test the model. To ensure that every data set was used in the testing, this procedure was repeated five times using the 5-fold cross validation approach. Two iterations of this entire cross-validation procedure were conducted to guarantee that the division would not produce skewed training and testing data sets. For this, an average confusion matrix was produced.
Figure provides an illustration of this procedure.



k-Means Clustering:

There is no requirement to label the data for unsupervised learning. Because of this, clustering was done using the unclassified data set, which had 2000 photos. Scale Invariant Feature Transformation (SIFT) was used to create a feature vector for every image [15]. The k-means clustering technique was used to divide this collection of feature vectors into two groupings. An algorithmic implementation in Matlab was employed. Since it was known that the data set contained two different types of items (cars and aircraft), two clusters were selected. Using the created cluster's silhouette values, the quality of the clusters was determined. To get the desired results, the clustering process is carried out ten times.



4. RESULTS AND ANALYSIS

A literature review was conducted as outlined in Section 3.1 in order to address the research question (RQ1). In Section 3.1, the appropriate supervised and unsupervised learning techniques were determined and made available.
The results of the experiment, which is detailed in Section 3.2, contain the answers to RQs 2 and 3. This chapter presents and analyzes these findings.

4.1 Experiment Results

Every algorithm was put into practice during the two halves of the experiment. This section presents the findings from each of the separate experiments.

4.1.1 Support vector machine classification

Using a dataset of 2000 photos, the object classification job was carried out, and the model was assessed twice through the use of 5-fold cross validation.
Table 4.1 displays the confusion matrices for every fold in this evaluation. The average confusion matrix in Table comes next.

Iterations	Folds	Known	Predicted: cars	Predicted: 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%

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

4.1.2 k-Means clustering

The silhouette score was used to assess the grouping. The cluster validity is shown by the silhouette score [13]. After ten cycles of clustering, the average silhouette score was calculated. Table presents these findings.

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

4.2 Analysis

Finding and evaluating results is just as vital as gathering them [16]. The examination of the outcomes found in part is covered in Section 4.1.

4.2.1 Support vector machine classification

Equation was used to determine the classifier's accuracy for each of the five folds in each iteration based on the confusion matrices in Table. Since there is no imbalance between the classes, the accuracy numbers offer a useful assessment of the classification. Table displays these.

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

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%

99.3% was determined to be the SVM classifier's average accuracy. Low dispersion in the observed results is indicated by the values' 0.12 standard deviation. This suggests that the classifier created is highly accurate.

4.2.2 k-Means clustering

By calculating the mean of the silhouette scores obtained from each iteration in Table, the average silhouette score for the clustering algorithm was determined. The average silhouette value of 0.3237 was determined. It was discovered that the standard deviation for these was 0.0003.

A cluster's silhouette value falls between -1 and +1. A better cluster is indicated by a higher value. The silhouette score, which is determined by using the rules outlined in Table 4.5, can be used to assess the quality of the cluster. These standards were established in [20].

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

The silhouette score of the used k-means cluster is 0.3237. This suggests that the generated clusters are part of a fragile framework.

4.2.3 Normalization of results

The two approaches' respective results fall into distinct scales. Equation 2 was used to normalize them to a standard scale of 0 to 100 in order to make a comparison. Table displays the values that have been standardized.

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

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**

The supervised SVM classifier yielded a normalized value of 99.30, whereas the unsupervised k-means clustering produced a normalized value of 66.18.

5. DISCUSSIONS

Discussions on the experiment's results are covered in this section of the report. This section goes into detail on the dangers to the validity of this research as well as its limitations. The responses to the research questions are also included in addition to this.
One of the main challenges in the rapidly developing field of image processing is object recognition. It is used in several fields, one of which being satellite imaging. Satellite photos can be processed using existing object identification algorithms. It was still unclear, nevertheless, how supervised and unsupervised methods compare to one another in this task. This is what the current investigation aimed to determine.

By examining the extant literature, a number of algorithms were found. Support vector machines and k-means classification were chosen from among them for this investigation. These algorithms' Matlab implementations were used to carry out the experiment.

The experiment's results, when analyzed, show that the results of the support vector machine classification are extremely accurate. However, the k-means clustering method produced a weak cluster, suggesting that there wouldn't be a lot of proximity between the components in each cluster in the clustered data. Accuracy and k-means with silhouette score were used to evaluate the SVM. Since there isn't a common meter for comparison, the optimal measure for each method was determined separately. The evaluation metrics selected offer a decent depiction of the algorithms' performance. To make comparing the algorithms easier, the findings are also normalized to a similar scale. These findings suggest that support vector machines outperform k-means clustering in the task of item detection in satellite photos. This is supported by the normalized values, silhouette scores, and accuracy, which demonstrate that the SVM classifier is more valuable than the k-means clustering. Based on the standard deviation data, it is also found that the accuracy and silhouette score have a limited spread.

This tells us that when it comes to object recognition in satellite photos, SVM performs better than k-means clustering. To fully understand how different algorithms compare to one another, this research might be expanded to include other algorithms.

5.1 Threats to validity

The investigation was conducted methodically, which reduced the hazards to the validity of the study. The following actions were done to mitigate.

Internal validity:

When the literature review or the experimentation are done incorrectly, internal validity may suffer.

- After a thorough examination of the literature, the algorithms were selected based on the way their performance was reported in previous studies. The algorithms used were those that were thought to be more appropriate for satellite picture object recognition.

- To make sure that every image is tested in one of the iterations, the classification experiment was carried out and assessed using 5-fold cross validation. In order to prevent any potential advantageous division, this was done twice.
- After ten iterations of clustering, the observed outcome was determined by taking the mean of the silhouette score.

External validity:

Two different object kinds were used to create the data set. If other object kinds are taken into consideration, the research might not be applicable. Choosing broad feature selection techniques that weren't object-type-specific was how this was resolved.

5.2 Limitations

Constrained areas of this study include the following.

- This study's purview was restricted to the identification and assessment of a just two algorithms. The conclusions were produced using the observations derived from the outcomes of these two algorithms.
- The algorithms' metrics cannot be directly compared. By standardizing the values to indicate a common scale, this is somewhat addressed.
- Methods for generic feature selection were used in the experiments. There are already methods in place that are tailored to certain kinds of objects. Since the goal of this study was to assess the algorithms for general object recognition, these were disregarded.

6. Conclusion and Future Work

6.1 Conclusion

A great deal of information may be found in satellite imagery. However, this data must be retrieved from the raw image data in order to be used. One technique that can aid in the information extraction from satellite photos is object recognition. Two methods for object recognition—one supervised and the other unsupervised—were selected based on how well they performed in previous investigations. As part of this work, these algorithms were then assessed using satellite photos. Using a two-object data set, support vector machines and k-means clusters were utilized to compare their performances and determine which method performed better overall. It was discovered that k-means clustering underperformed support vector machines using the normalized data.

These findings suggest that unsupervised k-means clustering is less suitable for object recognition on satellite photos than the supervised technique using support vector machines.

6.2 Future work

By implementing and assessing other object identification algorithms to determine their effectiveness, this study can be improved even more. In addition, future studies can examine the effects of selecting features based on database objects on the final outcomes.

REFERENCES

[1] Y. Ke *et al.*, “A Rapid Object Detection Method for Satellite Image with Large Size,” in *Multimedia Information Networking and Security, 2009. MINES’09. International Conference on*, 2009, vol. 1, pp. 637–641.
[2] N. Bouaynaya, W. Qu, and D. Schonfeld, “An Online Motion-Based Particle Filter for Head Tracking Applications.,” in *ICASSP (2)*, 2005, pp. 225–228.
[3] M. I. Sina, P. Payeur, and A.-M. Cretu, “Object recognition on satellite images with biologically-inspired computational approaches,” in *Applied Computational Intelligence and Informatics (SACI), 2012 7th IEEE International Symposium on*, 2012, pp. 81–86.
[4] J. Antelo, G. Ambrosio, J. González, and C. Galindo, “Ship detection and recognitionin high-resolution satellite images,” in *Geoscience and Remote Sensing Symposium, 2009 IEEE International, IGARSS 2009*, 2009, vol. 4, pp. IV–514.
[5] J.-W. Hsieh, J.-M. Chen, C.-H. Chuang, and K.-C. Fan, “Aircraft type recognition in satellite images,” in *Vision, Image and Signal Processing, IEE Proceedings-*, 2005, vol. 152, pp. 307–315.
[6] T. Blaschke, “Object based image analysis for remote sensing,” *ISPRS J. Photogramm. Remote Sens.*, vol. 65, no. 1, pp. 2–16, 2010.
[7] D. H. A. Al-Khudhairy, I. Caravaggi, and S. Giada, “Structural damage assessments from Ikonos data using change detection, object-oriented segmentation, and classification techniques,” *Photogramm. Eng. Remote Sens.*, vol. 71, no. 7, pp. 825–837, 2005.
[8] A. Rosenfeld, “Image pattern recognition,” *Proc. IEEE*, vol. 69, no. 5, pp. 596–605, May 1981.
[9] F. Tsutsumi and C. Nakajima, “Hybrid approach of video indexing and machine learning for rapid indexing and highly precise object recognition,” in *Image Processing, 2001. Proceedings. 2001 International Conference on*, 2001, vol. 2, pp. 645–648.
[10] Y. Kodratoff and S. Moscatelli, “Machine learning for object recognition and scene analysis,” *Int. J. Pattern Recognit. Artif. Intell.*, vol. 8, no. 01, pp. 259–304, 1994.
[11] T. O. Ayodele, *Machine learning overview*. INTECH Open Access Publisher, 2010.
[12] “ArcGIS.” [Online]. Available: http://www.arcgis.com/. [Accessed: 10-Jun-2016].
[13] “Flightradar24.” [Online]. Available: https://www.flightradar24.com/. [Accessed: 10-Jun-2016].
[14] T. Santha and others, “The significance of Real-time, biomedical and satellite Image Processing in understanding the objects & application to Computer Vision,” in *Engineering and Technology (ICETECH), 2016 IEEE International Conference on*, 2016, pp. 661–670.
[15] D. Michie, D. J. Spiegelhalter, and C. C. Taylor, “Machine learning, neural and statistical classification,” 1994.
[16] P. Flach, *Machine learning: the art and science of algorithms that make sense of data*. Cambridge University Press, 2012.
[17] S. J. Russell, P. Norvig, J. F. Canny, J. M. Malik, and D. D. Edwards, *Artificial intelligence: a modern approach*, vol. 2. Prentice hall Upper Saddle River, 2003.
[18] L. Eikvil, L. Aurdal, and H. Koren, “Classification-based vehicle detection in high-resolution satellite images,” *ISPRS J. Photogramm. Remote Sens.*, vol. 64, no. 1, pp. 65–72, Jan. 2009.
[19] Z. Sun, Z. Liu, S. Liu, Y. Zhang, and B. Yang, “Active learning with support vector machines in remotely sensed image classification,” in *Image and Signal Processing, 2009. CISP’09. 2nd International Congress on*, 2009, pp. 1–6.
[20] X. Huihui, X. Qizhi, and H. Lei, “A sea-land segmentation algorithm based on Gray Smoothness Ratio,” in *Earth Observation and Remote Sensing Applications (EORSA), 2016 4th International Workshop on*, 2016, pp. 117–121.