

A Supervised Stable Object Detection with Image Feature Extraction using Image Segmentation by Comparing Histogram of Oriented Gradients (HOG) Algorithm over Scale Invariant Feature Transform (SIFT) Algorithm Model.

M.Srikar¹, K. Malathi²

¹Research Scholar, Department of Computer Science and Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Saveetha University, Tamil Nadu, India, PinCode: 602105

²Project Guide, Corresponding Author, Department of Computer Science and Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Saveetha University, Tamil Nadu, India, PinCode: 602105

Abstract

Aim: The objective of the research is to increase the accuracy of object detection using novel image segmentation using machine learning algorithms. **Materials and Methods:** The categorising is performed by adopting a sample size of $n = 10$ in Histogram of Oriented Gradients (HOG) and sample size $n = 10$ in Scale Invariant Feature Transform (SIFT) algorithms with a sample size = 10 and the G-Power analysis was carried out with 80% and confidence interval 95%. **Results and Discussion:** The analysis of the results shows that the Histogram Of Oriented Gradients (HOG) has a high accuracy of 92.49% in comparison with the Scale Invariant Feature Transform (SIFT) 86.30%. A statistically significant difference exists between the research groups with $p=0.001$ (2 tailed) ($p<0.05$). **Conclusion:** Detection of objects with high accuracy using machine learning algorithms shows that the regional proposal network based Faster R-CNN appears to generate better accuracy than the Selective search(Fast RCNN) algorithm.

Keywords: Object Detection, Support Vector Machine (SVM), Histogram of Oriented Gradients, Image Segmentation, Novel Feature Descriptor, Invariant Feature Transform.

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INTRODUCTION

In today's highly competitive environment, computer vision is critical for identifying things with higher speed and precision. The goal of the research is to improve the accuracy of identifying objects and image segmentation using deep learning algorithms such as Histogram of Oriented Gradients and Scale Invariant Feature Transform (Anitha et al. 2016). Computer vision's major process is object detection, it is quite a complex problem for a system (Arulprakash and Aruldoss 2021). Computer vision is a major thing in this daily changing world with content-based image retrieval, machine vision, medical imaging, self-driving cars to face recognition in our mobiles, traffic detections, and many more security purposes (El-Baz, Jiang, and Suri 2016). The goal was to develop an inexpensive object detection system and boost its accuracy and speed to detect objects faster and more accurately (Novotny and Matas 2015).

Identifying objects using different image segmentation algorithms from many years and various surveys on detection and segmentation have been published in the last years over 20,600 articles from Google Scholar, 7782 journals from IEEE Xplore, 18,339 research articles from ScienceDirect. Among all the research articles and journals, the most cited paper is (Nilsback and Zisserman 2008). The model proposed by Nilsback and Zisserman is very advanced and improved to extract low level features of a given input image compared to the models with different classifiers and features. The proposed Novel feature descriptor creates a very discriminating feature for

describing picture content (Wang et al. 2021). Different datasets and processed images applied to test the proposed model capability (Vohra and Prodanov 2021). A Novel feature descriptor helps the model to detect detail based picture recapture using scale invariant feature transforms and oriented gradient pattern (Giveki, Soltanshahi, and Montazer 2017).

Our institution is passionate about high quality evidence based research and has excelled in various fields (Parakh et al. 2020; Pham et al. 2021; Perumal, Antony, and Muthuramalingam 2021; Sathiyamoorthi et al. 2021; Devarajan et al. 2021; Dhanraj and Rajeshkumar 2021; Uganya, Radhika, and Vijayaraj 2021; Tesfaye Jule et al. 2021; Nandhini, Ezhilarasan, and Rajeshkumar 2020; Kamath et al. 2020). This method which was used before has less accuracy in segmenting objects. It is necessary to determine and segment the object to identify in very less time to prevent issues. For example, a common use for image segmentation in medical purpose photographs is to detect and label 3D volume images or pixels in voxels that represent tumours in the patient's body. The research gap found to be the low accuracy and constant speed to identify the object is lacking in the previous model. Different attributes proposed in the previous system have become less efficient as the environment changes. In order to sequence the methods and techniques in this proposed model is generally much better than the scale invariant because it takes a lot more time to train the dataset. Novel feature descriptors help to detect homogeneous features in a picture. Texture features are a very useful characterization for a wide range of images used in this model. Texture features may be widely classified into spatial texture function extraction strategies and spectral texture features extraction strategies primarily based totally at the domain from which they may be extracted. In the primary approach, texture features have become extracted with the aid of computing the pixel data or with the aid of locating the neighbourhood pixel systems in the original photograph domain (Hung, Song, and Lan 2019).

MATERIALS AND METHODS

The research was carried out in the Image Processing Lab, Department of Computer Science and Engineering, Saveetha School of Engineering, SIMATS. Basically it is considered with two groups of classifiers namely Histogram of Oriented Gradients (HOG) and Scale Invariant Feature Transform (SIFT) algorithms, To identify objects in the photo with various datasets and labels. Group 1 is the Histogram of Oriented Gradients (HOG) with the sample size of 10 and Group 2 is the Scale Invariant Feature Transform (SIFT) with sample size of 10 and it was used to compare for more accuracy score values for choosing the best algorithm to detect objects correctly. Sample sizes of 20 different values are used along with an alpha as 0.05 and beta as 0.2, 95% confidence interval and with G-power having 80%, and identified as standard deviation for Histogram of Oriented Gradients (HOG) = .32554 and Scale Invariant Feature Transform (SIFT) = .45535.

The dataset used in the model for prediction process has been collected from the Kaggle website. The dataset can be found as the Fruit Recognition dataset created by the owner (Chris Gorgolewski). The dataset contains different label images around 660 files of apple class labels and equally other class labels named Class A and Class B respectively. The images were collected in various kinds of conditions to obtain accurate results even under different low light conditions. The data is further processed for training and testing datasets and has been split up in the ratio of 70% and 30% respectively. Adapting Google Collaboration as the software which will provide a wide Range of GPUs. The Gpu used is the Nvidia Tesla K80. The configurations of the system used are Intel i5, 5th Gen CPU@2.8GHZ, 8 GB RAM, and 64-bit OS.

Histogram Of Oriented Gradients (HOG) Algorithm.

The primary model is developed using Histogram of Oriented Gradients (HOG) algorithm. HOG are Novel feature descriptors that can be utilised in image segmentation for item identification purposes. In this paper, the HOG developed with support vector machine; a feature descriptor obtain the item features in the picture and those were used to classify the items (Liang, Wang, and Zhang 2015). This approach counts the number of times the gradient outlook appears in a certain area of the picture. This technique sounds quite the same as edge plotting, HOG descriptors analyse the image and find the item configurations and propositions. It outperforms all other edge descriptors because it computes features based on both the proportions and angle of the gradient. Certain area measures are consider for the picture, it creates a histogram using dimensions and angle of the gradient. From the input picture the gradient will be evaluated.

The grey area or the gradient coordinates is formed by the descriptor after analysing the image. Taking a length of 3×3 pixels as coordinate box, For every box in gradient it will be evaluated initially by considering GX and Gy. The initial Gx and Gy are analysed by the formulas to every pixel box. The Gx and Gy are the change in

gradients respective towards the outlook. The approach sums up the instances of gradient orientation in certain areas of a picture and trained classifiers using different datasets will recognize the objects in the picture. By detecting the features in the picture and these features will be given to the classifier. In this model we take the Support Vector Machine (SVM) classifier. Support Vector Machine (SVM) classifiers look for efficient hyperplanes as a decision function, the classifier outputs the feature that matches the training datasets the best.

Pseudocode

Step 1: Import keras, cv2.
Step 2: Ready Train Dataset to feed into the model.
Step 3: Train_val images → Conv2D, MaxPooling2D
Step 4: Image → cv2.imread(path_train[5])
Step 5: collect the gradient image → (image,cv2.color_BGR2RGB)
Step 6: Svm_hog → sequential()
Step 7: Svm_hog.add(Conv2D(32,(3,3),input_shape=(50,50,3),activation="relu"))
Step 8: receive the image from the hog classifier → (hog_image, in_range=(0, 10))
Step 9: plt.show()
Step 10: Accuracy of the proposed model.

Scale Invariant Feature Transform (SIFT) Algorithm.

Another approach to achieving the local descriptor is Scale Invariant Feature Transform (SIFT) Algorithm. This method converts picture data into relative scale invariant dimensions according to the specific characteristics of the locality and revolves around four main stages: detect extreme points in space, position of key points, orientation like signature descriptor and keypoint (Invariant Feature Transforms) (Goncalves, Corte-Real, and Goncalves 2011). The segmentation is carried out by looking across all dimensions and picture locations for prospective interest spots that are scale and orientation insensitive. After obtaining a list of feature point prospects, the following step is to precisely locate them. This is accomplished by discarding keypoints with low contrast or that are imperfectly localised on an edge, as well as a precise fit to the neighbouring data for arrangement, size, and major curvature ratio. So simply one should strive matching patches round the salient characteristics points, however those patches will themselves alternate if there's alternate in object pose or illumination. So those patches will result in numerous false matches and correspondences.

Pseudocode

Step 1: import matplotlib.pyplot as plt, keras.
Step 2: Train the model with Train_val dataset.
Step 3: feeding the dataset to the model → Conv2D, MaxPooling2D
Step 4: image = cv2.imread(path_train[5])
Step 5: for path in path_test: img = cv2.imread(path)
Step 6: ConvolveImageGaussParallel();
Step 7: For each pixel p in the picture, detect Keypoint pragma omp parallelly.
Step 8: Extracted points values will feed into the final layer.
Step 9: from sklearn import preprocessing
Step 10: print final prediction value.

Statistical Analysis

IBM SPSS (version 26) statistical tool is used for analysis. 10 iterations were done with a sample size of 10 for each of the algorithms and predicted accuracy was noted for analysis. And the sample size was calculated using G power of 80% for each group and confidence interval of 95% for the two groups. Group id 1 for HOG algorithm and Group id 1 for SIFT are given. The value obtained from the iterations of a total 20 samples 10 iterations from each of the algorithms and conducted Independent Sample T-test using SPSS statistical tool. The dependent data sets are ImageNet, Microsoft COCO test-dev, PASCAL VOC 2007. The independent values are AlexNet, VGGNet (Mizuno et al. 2012). The fragmented analysis has been done with independent variables labelled images, bounding box coordinates and dependent variables are accuracy, duration, feature graded object graph, val_loss and val_accuracy to find the objects with more accuracy and speed.

RESULTS

The model has trained through more than 660 files on specific labels. Group statistics of Histogram Of Oriented Gradients (HOG) of by Scale Invariant Feature Transform (SIFT) by grouping with iterations sample size of 10 is displayed in Table 1, mean = 92.4919 Standard Deviation = 0.36961 , Standard Error Mean = 0.11688.

In table-2, The statistical analysis of two independent groups shows that the Histogram Of Oriented Gradients (HOG) have higher accuracy mean 92.49% compared to selective search based Scale Invariant Feature Transform (SIFT) with accuracy 86.30%.

In Table-3, The Significant value= 0.125, Mean Difference= 6.1879 and confidence interval = (5.52833 - 6.84747) of Histogram Of Oriented Gradients (HOG) based Object detection and Scale Invariant Feature Transform (SIFT) based Object detection is tabulated in Table 2, The significance value is $p=0.001$ ($p<0.05$) with an independent sample T-Test. Images, labels and tested image datasets independent variables. The dependent variables in object detection are detected with the help of the independent variables.

Figure 1, represents the mean accuracy of Histogram Of Oriented Gradients (HOG) and Scale Invariant Feature Transform (SIFT) Algorithms in a simple bar graph. The Histogram Of Oriented Gradients (HOG) system has scored 92.49% accuracy and the Scale Invariant Feature Transform (SIFT) has obtained 86.30% accuracy. The Histogram Of Oriented Gradients (HOG) technique has achieved better performance than Scale Invariant Feature Transform (SIFT).

DISCUSSION

This work on identifying items in pictures, subsequently termed object detection, is very essential in many industries in order to comprehend different scenarios by computer systems (Pathak, Pandey, and Rautaray 2018). The most important function of identifying an item using Histogram Of Oriented Gradients (HOG) (Ren et al. 2017) is pragmatically proven to be more effective than Scale Invariant Feature Transform (SIFT). The core argument is to prove that detection of objects using image segmentation techniques may be a better method than other methods to extract image features which helps to identify the items easily. The mean accuracy is 92.79% using HOG and 86.30% using SIFT. And the statistical 2-tailed significant difference in accuracy for two algorithms is 0.001 ($p<0.05$). In many of the recent findings, it has been observed that a novel feature descriptor by HOG model using a support vector machine is the most focused and better method of extracting image gradients and with more accuracy than SIFT (Zhou et al. 2021).

The purpose of computer vision is to reach a very top level of determining objects through photos and videos. Previous and old view methods that take a completely rendered colour image as input. However, in situations where colour is not needed such as gradient-based algorithms discussed in this article, decoding is pointless. It is time consuming and also wasteful of storage space to get almost the same result considering the colours of the image. So these algorithm models consider the input image and convert it into grey and extract image features and gradients. For colour images, grey scale images are generated for gradient extraction.

Based on the discussion, limitations can be overcome by the use of descriptors in HOG model improves the accuracy and achieves an advanced level of image segmentation. The drawback of the previous models was that the identification of images is obsolete, which consumes a lot of storage and time taking. The model will consider the input image and extract the coordinates of the object underlined in it but the actual problem behind this approach is that the classifiers took more space and process time to scan each image that has different colors as we don't need the image unnecessary properties but the actual gradient properties will enough to the new approach to identify the object. HOG descriptors generated from colour and pattern pictures outperform SIFT descriptors, the HOG with support vector machine (SVM) framework has been proposed in this model and used to detect the fruit images from various datasets provided. The models are trained using different dataset images under various conditions to identify objects with precision. The outcome is decided with precision-recall curves. And the feature score is extracted, and is searched among a 5×5 neighbourhood in place of 3×3 . To verify that the resulting SIFT features critical points recognised from the modified pictures are scale and rotation invariant, i.e the image is scaled and blurred. Main attractions matched with what was detected from pictures. The SIFT descriptor's performance in finding the dots match was evaluated using the repeatability criterion provided in. For future enhancement of the system, richer picture datasets and powerful processors might be used to maintain a balanced accuracy and speed.

CONCLUSION

The objective of the work is to increase the accuracy of object detection using novel image segmentation using machine learning algorithms. The accuracy and speed is improved significantly by use of the feature descriptor function in the HOG model. The outcome of the Histogram of Oriented Gradients algorithm showed higher accuracy 92.49% than the Scale Invariant Feature Transform algorithm 86.30%.

DECLARATION

Conflicts of Interest

No conflicts of interest in this manuscript.

Authors Contribution

Author MS was involved in data collection, data analysis, algorithm framing, implementation and manuscript writing. Author KM was involved in designing the workflow, guidance and Critical review of the manuscript.

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Tables And Figures

Table 1. Accuracy values of HOG and SIFT models. The HOG obtained accuracy of 92.49% compared to SIFT having 86.30%. The significant 2-tailed value for the two groups is $P = 0.001$ ($p < 0.05$).

Sample (N)	Dataset size	HOG	SIFT
1	660	93.24	87.25
2	572	91.86	86.28
3	510	92.97	86.91
4	456	93.18	85.71
5	332	92.23	86.99
6	287	91.10	87.10
7	240	93.00	85.53
8	135	91.55	85.08
9	122	91.74	85.18
10	77	93.68	87.28

Table 1. Group Statistics of Histogram Of Oriented Gradients (HOG) by grouping the iterations with sample size 6, Mean = 92.4919, Standard Deviation = 0.36961. Descriptive Independent Sample Test of Accuracy is applied for the dataset in SPSS.

	Group	N	Mean	Std. Deviation	Std. Error Mean
Accuracy	HOG	10	92.4919	0.36961	0.11688
	SIFT	10	86.304	0.9214	0.29137

Table 2. Independent Sample T-Test is applied for the dataset fixing confidence as 95% and level of significance as $P = 0.001$ ($p < 0.05$).

Levene's test for equality of variances	t-test for Equality of Means

	F	Sig.	t	df	Sig.(2-tailed) p	Mean Difference	Std. Error Difference	95% confidence interval of the difference	
								Lower	Upper
Equal variances assumed	2.59	0.125	19.71	18	0.001	6.1879	0.31394	5.52833	6.84747
Equal variances not assumed			19.71	11.823	0.001	6.1879	0.31394	5.50274	6.87306

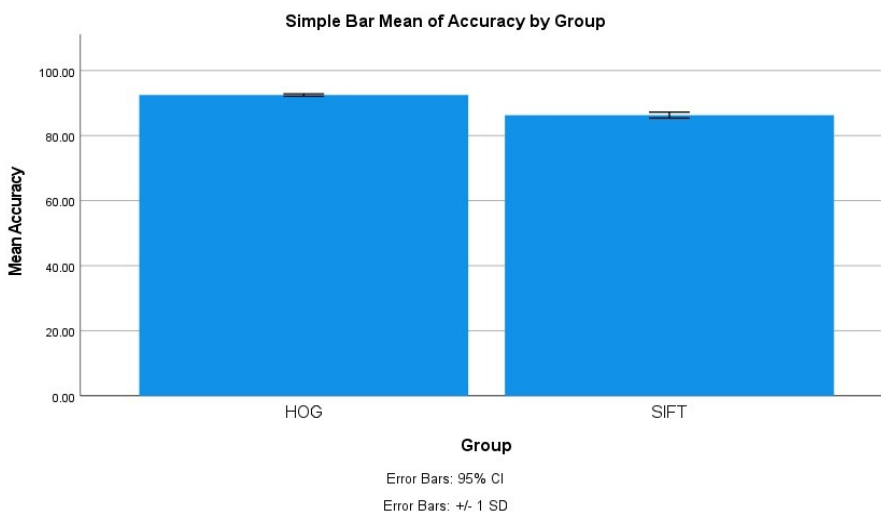


Fig. 1. Comparison of regional proposal network based HOG in terms of mean accuracy. As the graph shows the mean accuracy of the HOG is greater than the SIFT. Graphical representation of the bar graph is plotted using group id as X-axis HOG vs SIFT, Y-axis displaying the error bars with mean accuracy of detection +/-1 SD.