**Title Page:**

# An Improved Moving Object Detection In A Wide Area Environment Using Image Classification And Recognition By Comparing You Only Look Once (YOLO) Algorithm Over Deformable Part Models (DPM) Algorithm.

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**Keywords:** Object Detection, Deformable Part Model, Novel Image Classification, Bounding Boxes.Fast Convolutional Neural Network.

**ABSTRACT**

**Aim:** The aim of the research work is to improve the accuracy of object detection using novel image classification using machine learning algorithms. **Materials and Methods:** The categorisingis performed by adopting a sample size of n = 10 in You Only Look Once (YOLO) and sample size n = 10 in Deformable Part Model (DPM) algorithms with a sample size = 10. **Results and Discussion:** The analysis of the results shows that the You Only Look Once (YOLO) has a high accuracy of (90.7899 %) in comparison with the (83.475 %). There is a statistically significant difference between the study groups with (p<0.05). **Conclusion:** Detection of objects with high accuracy using machine learning algorithms shows that the You Only Look Once (YOLO) appears to generate better accuracy than the Deformable Part Model (DPM) algorithm.

**Keywords:** Object Detection, Deformable Part Model, Novel Image Classification, Bounding Boxes.

**INTRODUCTION**

The effectiveness of region proposal approaches and region-based convolutional neural networks has fueled recent breakthroughs in object detention(R-CNN). The purpose of this research is to improve the Accuracy of object detection in computer vision through image classification using machine learning algorithms by using a You Only Look Once(YOLO)[(I and Ankith 2021)](https://paperpile.com/c/Dwd9Ii/gou6). Object Detection is an important task in computer vision, it is one of the most complex tasks for a computer system[(Arulprakash and Aruldoss 2021)](https://paperpile.com/c/Dwd9Ii/IQSTZ). Since computer vision is a major thing in the trending world with self-driving cars, traffic detections, tracking objects and many security purposes[(Jiang et al. 2018)](https://paperpile.com/c/Dwd9Ii/GCU3). In simple words, image classification is a technique that is used to classify or predict the class of a specific object in an image, and used in medical imaging, object identification in satellite images, traffic control systems, and brake light detection. The goal is to develop a low cost object detection model and improve accuracy and faster and more accurate object detection[(Novotny and Matas 2015)](https://paperpile.com/c/Dwd9Ii/wfa3Z).

Predicting objects using object detection algorithms for over past years and several surveys and detection and recognition have been published in the last years over 13,900 articles from google scholar, 658journals IEEE Xplore digital library 571 research articles from science direct. Among all the articles and journals, the most cited paper is [(He et al. 2015)](https://paperpile.com/c/Dwd9Ii/IuPm). The model produced by the [(Redmon and Farhadi 2017)](https://paperpile.com/c/Dwd9Ii/9wwe) is very accurate and with improved speed compared to the Deformable Part Models algorithm[(Tang 2016)](https://paperpile.com/c/Dwd9Ii/cTPy). In this paper the YOLOv3 algorithm uses a totally different approach. We apply a single neural network to the full image. This network divides the image into regions and predicts bounding boxes and probabilities for each region. These bounding boxes are weighted by the predicted probabilities [(Adarsh, Rathi, and Kumar 2020)](https://paperpile.com/c/Dwd9Ii/6nsU). It looks at the whole image at test time so its predictions are informed by global context in the image. It also makes predictions with a single network evaluation unlike systems likeR-CNN which require thousands for a single image. This makes it extremely fast, more than 1000x faster than R-CNN and 100x faster than Fast R-CNN and DPM algorithm [(Kitano, Takiguchi, and Ariki 2015)](https://paperpile.com/c/Dwd9Ii/1zPG).

This approach which was used earlier has much less accuracy on detection objects. It is important to hit upon and detect the item in very milliseconds to save you problems. For example, self-riding vehicles want to detect the items in a fragment of seconds and analyse the image to move forward, in any other case there might be many consequences. In order to collect the techniques and strategies on these studies usually stands far higher than the R-CNN algorithm. It additionally takes plenty of extra time to render all of the images to teach the version in comparison to YOLOv3 to DEFORMABLE PART MODELS algorithm . The aim of the research work is to improve the accuracy of object detection using the You Only Look Once(YOLO) algorithm over a Deformable Part Models(DPM) algorithm.

**MATERIALS AND METHODS**

The research work was performed 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 YOLOv3 and DPM algorithm which is used to detect objects in the image with various image datasets and labels. Group 1 is the YOLOv3 with the sample size of 10 and Group 2 is the DPM with sample size of 10 and it was used to compare for more accuracy score and loss values for choosing the best algorithm to detect objects correctly. Sample size has been calculated and it is identified as standard deviation for YOLOv3 =.32554 and DPM = .45535.

**YOLO ALGORITHM**

You Only Look Once(YOLO) is a state-of-the-art, real-time object detection system. YOLOv3 is extremely fast and accurate. In mAP measured at .5 IOU YOLO v3 is on par with Focal Loss but about 4x faster. Moreover, you can easily trade off between speed and accuracy simply by changing the size of the model, no retraining required. Prior detection systems repurpose classifiers or localizers to perform detection. They apply the model to an image at multiple locations and scales. High scoring regions of the image are considered detections. In this paper we used a totally different approach. We apply a single neural network to the full image. This network divides the image into regions and predicts bounding boxes probabilities for each region. These bounding boxes are weighted by the predicted probabilities. This model has several advantages over classifier-based systems. It looks at the whole image at test time so its predictions are informed by global context in the image.It also makes predictions with a single network evaluation unlike systems like R-CNN which require thousands for a single image. This makes it extremely fast, more than 1000x faster than R-CNN and 100x faster than Fast R-CNN and DPM. YOLOv3 uses a few tricks to improve training and increase performance, including multi-scale predictions, a better backbone classifier, and more. By using open CV2 the predicted bounding box images are classified and obtained output.

**Pseudocode for YOLO Algorithm**

import tensorflow as tf

import numpy as np

from PIL import Image, ImageDraw, ImageFont

from IPython.display import display

from seaborn import color\_palette

import cv2

image → readImage()

NoOfCells → 7

threshold → 0.7

step → height(image)/NoOfCells

prediction\_class\_array → new\_array(size(NoOfCells,NoOfCells,NoOfClasses))

predictions\_bounding\_box\_array→new\_array(size(NoOfCells,NoOfCells,NoOfCells,NoOfCells))

final\_predictions → []

for (i<0; i<NoOfCells; i=i+1):

for (j<0; j<NoOfCells;j=j+1):

cell → image(i:i+step,j:j+step)

prediction\_class\_array[i,j] → class\_predictor(cell)

predictions\_bounding\_box\_array[i,j]→bounding\_box\_predictor(cell)

best\_bounding\_box → [0 if predictions\_bounding\_box\_array[i,j,0, 4] > predictions\_bounding\_box\_array[i,j,1, 4] else 1]

predicted\_class → index\_of\_max\_value(prediction\_class\_array[i,j])

Ifpredictions\_bounding\_box\_array[i,j,best\_bounding\_box,4]\*max\_value(prediction\_class\_array[i,j]) > threshold: prediction→[predictions\_bounding\_box\_array[i,j,best\_bounding\_box, 0:4], predicted\_class] final\_predictions.append(prediction)

print final\_predictions

**DEFORMABLE PART MODELS(DPM) ALGORITHM**

The Deformable part model is one of the most popular object detection methods.It was originally proposed for the Pascal VOC challenge. DPM has the advantage in handling large appearance variations for challenging datasets, however, it takes more than 10 seconds per image in Pascal VOC. The speed is a bottleneck of DPM in real application, where speed is often as important as accuracy. The DPM approach is far different from the YOLO approach, DPM related approaches that accelerate single category DPM in object detection proposed to convert star-structure to cascade-to-fine approach based on that model at low resolution can prune a lot of hypotheses with low computational cost [(Yan et al. 2014)](https://paperpile.com/c/Dwd9Ii/ciqL). The model is based on deformable models that represent objects using local part templates and geometric constraints on the locations of parts. We reduce object detection to classification with latent variables. The latent variables introduce invariances that make it possible to detect objects with highly variable appearance. And also use a generalization of support vector machines to incorporate latent information during training. This has led to a general framework for discriminative training of classifiers with latent variables. Discriminative training benefits from a large training dataset [(P. Felzenszwalb et al. 2013)](https://paperpile.com/c/Dwd9Ii/8eOp). Deformable part models such as pictorial structures provide an elegant framework for object detection. Yet it has been difficult to establish their value in practice. While deformable part models can capture significant variations in appearance, a single deformable model is often not expressive enough to represent a rich object category. Consider the problem of modeling the appearance of bicycles in photographs.The system described here uses mixture models to deal with these more significant variations [(P. F. Felzenszwalb et al. 2010)](https://paperpile.com/c/Dwd9Ii/1ovl).

**Pseudocode for Deformable Part Model Algorithm.**

Import cv2

Import numpy as np

From skimage import io

Import math

From skimage.feature import hog

From skimage import data, color, exposure, transform

Initialize def \_\_init\_\_(

Self,

step\_x→4,

step\_y→2,

Self.image\_h → 22

Self.image\_w → 90

Self.step\_x → step\_x

Self.step\_y → step\_y)

Self.pix\_per\_cell\_root → pix\_per\_cell\_root

Self.cells\_per\_block\_part → cells\_per\_block\_part

Def train\_clf(self,X,Y,C, count kernel→’linear’, degree=3,coef0=0.0):

From sklearn.tree import DecisionTreeClassifier

adaboostclf=AdaBoostClassifier(DecisionTreeClassifier(max\_depth=2))

adaboostclffit(X,Y)

Def image\_fragment\_mag(self,mag\_map,rect):

im\_mag=mag\_map[rect[0]:rect[0]+rect[2],rect[1]:rect[1]+rect[3]]=0

Def process\_image(self, image, name = ‘’):

Height = len(image)

Width = len(image[0])

Im\_result = image.copy()

Y = 0

X = 0

While y in range(0,height -self.image\_h):

X = 0

Res=self.process\_frame(image[y:y+self.image\_h,x:x+self.image\_w])

If res:

cv2.rectangle(im\_result(x,y),(x+self.image\_w,y+self.image\_h)

Def test\_model:

input\_image=cv2.imread(‘CarData/TestImages?test-’+str(count)+’.pgm,0)

Inp = annotation.readline()

Inp = inp.split(‘ ‘)[1:]

Coords = []

Im\_neg1 = input\_image[0:0+40]

Im\_neg2 = input\_image[len(input\_image)-40:,len(input\_image[0])-100]

Recall = tp/(0.0+tp+fn)

precision = tp/(0.0+tp+fp)

accuracy = (tp + tn)/(0.0 + tp+fn+fp+tn)

f1 = 2\*precision \* recall/(precision + recall)

print('TEST\_\_VALID:','tp=',tp,'fp=',fp,"tn=",tn,"fn=",fn,"recall=",recall,"precision=",precision,"accuracy=",accuracy ,"f1=",f1)

**STATISTICAL ANALYSIS**

The analysis was done using IBM SPSS version 21. It is a statistical software tool used for data analysis. For both proposed and existing algorithms 10 iterations were done with a maximum of 10 samples and for each iteration the predicted accuracy was noted for analysing accuracy. The value obtained from the iterations of the Independent Sample T-test was performed. The dependent data sets are ImageNet, Microsoft COCO test-dev, PASCAL VOC 2007,PASCAL VOC 2012. The independent values are AlexNet, VGGNet, RetinaNet, ResNeXt-101-FPN. The fragmented analysis has been done with independent and dependent variables to find the objects with more accuracy and speed.

**RESULTS**

The Datasets used to train models are the COCO dataset, PASCAL VOC 2007, 2012 datasets. The model has trained through more than 22000 images on specific labels. Group statistics of You Only Look Once (YOLO) by Deformable Part Models (DPM) by grouping with iterations sample size of 10, mean = 90.7899 Standard Deviation = 1.07686 , Standard Error Mean = 0.34053. Descriptive Independent Sample Test of Accuracy and Loss is applied for the dataset in SPSS. Here it specifies equal variances with and without assuming a T-Test Score of two groups with each sample size of 10 in Table 2. The Significant value= 0.649, Mean Difference= 7.31490 and confidence interval = (6.23666 - 8.39314) of You Only Look Once (YOLO) based Object detection and Deformable Part Models (DPM) based Object detection is tabulated in Table 3, which shows there is a significant difference between the two groups since P<0.005 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. The statistical analysis of two independent groups shows that the You Only Look Once (YOLO) have higher accuracy mean (90.7899 % ) and Less Loss mean 1.1960 % compared to Deformable Part Models (DPM) with accuracy (83.4750 %) and Less Loss mean 1.9830 % in table-1.

**DISCUSSION**

In this paper, detecting objects in real time based on images, subsequently termed Object Detection using computer vision by machine learning algorithms is very important in many industries in order to process different scenarios [(Pathak, Pandey, and Rautaray 2018)](https://paperpile.com/c/Dwd9Ii/wytsF). For this purpose we are using various machine learning algorithms and deep learning methods such as YOLO in this research work. We present YOLO, a new approach to object detection. Prior work on object detection repurposes classifiers to perform detection. Instead, we frame object detection as a regression problem to spatially separated network predicts bounding boxes and class probabilities directly from full images in one evaluation. Since the whole detection pipeline is a single network, it can be optimised end to end directly on detection performance[(Redmon et al. 2016)](https://paperpile.com/c/Dwd9Ii/q9UY).

This unified architecture is extremely fast and processes images in real-time at 45 frames per seconds. A smaller version of the network, Fast YOLO processes an astounding 155 frames per second while still achieving double the mAP of other real-time detectors. So to put it simply, you take an image as input, pass it through a neural network that looks similar to a normal CNN, and you get a vector of bounding boxes and class predictions in the output. The first step in understanding YOLO is how it encodes its output. The input image is partitioned into an S x S grid of cells, and for each object in the image, one grid cell is said to be responsible for prediction. This is the cell where the centre of the object falls into. Once you understand how the predictions are encoded, the rest is easy. The network structure looks like a normal CNN, with convolutional and max pooling layers, followed by 2 fully connected layers in the end.

Object detection is an important capability for most computers and robotic vision systems. Although great progress has been made in recent years and some now part of many consumer electronic devices or already integrated into driver assistance technologies. We are still far from reaching human level performance, especially in open world study. It should be noted that object detection has not been used much in many areas where it could be helped a lot. As mobile robots and in general stand-alone machines, which are starting to become more widely available deployed(quadcopters, drones and early services robots), the need for an object detection system is more important. Finally, we must consider that we need advanced improvements in object detection and making machines capable of learning in the open world in real time independently[(Lu, Zhang, and Xie 2020)](https://paperpile.com/c/Dwd9Ii/0SbM).

**CONCLUSION**

An Improved Moving Object Detection In A Wide Area Environment Using Image Classification And Recognition By Comparing Yolo Algorithm Over Deformable Part Models (Dpm) Algorithm. The current study focused on machine learning algorithms,You Only Look Once(YOLO) algorithm over Deformable Part Model(DPM) for higher classification of object detection. It can be slightly improved based on high trained datasets in future. The outcome of the YOLO algorithm showed higher accuracy (90.7899% ) than the DPM algorithm(83.475%).

**DECLARATION**

**Conflict of Interests**

No conflict of interest

**Authors Contribution**

Author MS was involved in data collection, data analysis, manuscript writing. Author NM was involved in the Action process, Data verification and validation, and Critical review of manuscript.

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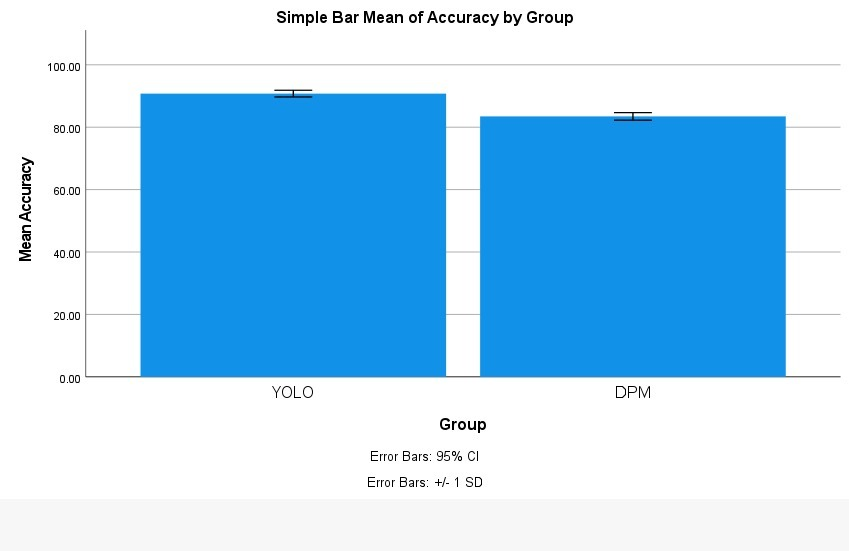
**TABLES AND FIGURES**

**Table-1.** Group Statistics of You Only Look Once(YOLO) by grouping the iterations with sample size 10, Mean = 90.7899, Standard Deviation = 1.07686. Descriptive Independent Sample Test of Accuracy and Loss is applied for the dataset in SPSS. Here it specifies Equal variances with and without assuming a T-Test Score of two groups with each sample size of 10.

|  | **Group** | **N** | **Mean** | **Std. Deviation** | **Std.Error Mean** |
| --- | --- | --- | --- | --- | --- |
| **Accuracy** | YOLO | 10 | 90.7899 | 1.07686 | 0.34053 |
|  | DPM | 10 | 83.475 | 1.21422 | 0.38397 |
| **Loss** | YOLO | 10 | 1.196 | 0.53674 | 0.16973 |
|  | DPM | 10 | 1.983 | 0.56255 | 0.1779 |

**Table-2.** Independent Sample Test of Accuracy and Loss (calculate P-value = 0.001 and Significant value = 0.234, Mean Difference = 3.5230 and confidence interval = (0.5338 - 0.7780). HOG and DPM are significantly different from each other.

|  |  |  | |  |  | **Significance** | |  |  | **95% confidence interval of the difference** | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  | **F** | **Sig.** | **t** | **df** | **One-sided p** | **Two-Sided p** | **Mean Difference** | **Std. Error Difference** | **Lower** | **Upper** |
| **accuracy** | **Equal variances assumed** | 0.214 | 0.649 | 14.253 | 18 | <.001 | <.001 | 7.3149 | 0.51322 | 6.23666 | 8.39314 |
| **Equal variances not assumed** |  |  | 14.253 | 17.747 | <.001 | <.001 | 7.3149 | 0.51322 | 6.23556 | 8.39424 |
| **Loss** | **Equal variances assumed** | 0.243 | 0.628 | -3.201 | 18 | 0.002 | 0.005 | -0.787 | 0.24588 | -1.30357 | -0.27043 |
| **Equal variances not assumed** |  |  | -3.201 | 17.96 | 0.002 | 0.005 | -0.787 | 0.24588 | -1.30365 | -0.27035 |

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**Fig. 1.** Comparison of regional proposal network based YOLO in terms of mean accuracy. It explores that the mean accuracy is slightly better than DPM with Selective search and the standard deviation is moderately improved compared to logistic regression. Graphical representation of the bar graph is plotted using group id as X-axis YOLO vs DPM, Y-axis displaying the error bars with mean accuracy of detection +/-1 SD.