Original Article

An Enhanced Object Detection in Integral Part of Computer Vision using object Localization by Comparing Spatial Pyramid Pooling Net Algorithm over R-CNN Algorithm.

M.Srikar[1], K. Malathi[2]

[1]Research 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
[2]Project 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 work is to increase the precision of detecting objects using inventive Object localisation and Deep Convolutional Neural Networks with machine learning algorithms. **Materials and Methods:** The categorising is performed by adopting a sample size of n = 10 in Spatial Pyramid Pooling net in R-CNN and sample size n = 10 in R-CNN algorithms with a sample size = 10 and the G-Power analysis was carried out with 80% and the confidence interval 95%. **Results and Discussion:** The observation of the outcomes shows that the R-CNN using spatial pyramid pooling net layer has a high accuracy of 85.43% in comparison with the Region based convolutional neural network 78.36%. 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 shows that the spatial pyramid pooling net layer based R-CNN generates higher accuracy than region based convolutional neural network algorithms.

Keywords: Object Detection, R-CNN, Deep Convolutional Neural Network, Novel Pyramid Pooling Layer, Object Localization, Deep Network, Spatial Pyramid Match.

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INTRODUCTION

In today's highly competitive environment, computer vision is critical for quickly and accurately identifying things and items in a picture. The capacity to automatically identify and separate such significant visual areas has direct implications for applications in computer vision (Gupta et al. 2020). The need of this research work is to make a model that is more efficient through object localization using deep network learning algorithms by using regional proposal networks. Spatial Pyramid Pooling (SPP) layer eliminates the network's definite size limitation, i.e. a deep convolutional neural network does not require a fixed size input picture (Li et al. 2020). Specifically, By adding an SPP layer before the last convolutional layer (Guo et al. 2018). A Deep network primarily based approach has lately been drastically enhancing upon the nation of the artwork in image classification, item detection, many different popularity tasks, or even non-popularity tasks (He et al. 2015). Specific object detection applications include pedestrian detection, video surveillance, text detection, pose direction, and many more. Through this model using Novel Pyramid Pooling Layer the object detectors and trackers have greatly improved the model, achieving significant standards in object localization (Zhang et al. 2021).

In detecting of objects through spatial pyramid match pooling layer by comparing over 17,300 journals from google scholar, 2,334 articles from science direct, 1,206 articles, 1,205 chapters, 794 conference papers from springer link, 135 journals from IEEE xplore digital library. The SPP layer has improved accuracy over R_CNN. Among all the articles and journals, the most cited paper is (He et al. 2015) is a most useful and improved. In this work, a novel idea of adding sppnet layer in the convolutional neural network was introduced by (He et al. 2015). By training the spatial pyramid match layer on PASCAL VOC 2007 there is an increase in speed up to 64 times faster over R-CNN and improved accuracy. SPPs are based on spatial pyramid matching model(SPM)(BoW) (Ismail et al. 2018). The input picture with any specified input is the main functioning of the SPP layer in the

neural network. The feature pooling layer will take the image as an input value (Gao, Shang, and Wu 2021). Further the outcome values of the input by the previous layer are considered by the SPP layer. It doesn't matter what the input picture coordinates, the SPP layer produces a fixed length output (Sun, Ni, and Zhao 2022)
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 technique which was utilised before has less precision on recognizing objects, minuscule items. It is important to distinguish and decide the object in very milliseconds to forestall issues. For instance, autonomous vehicles need to distinguish the object inside a small amount of seconds and dissect the circumstance to push ahead, in any case there will be numerous outcomes. 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. To arrange the strategies and procedures in this exploration for the most part fairs better compared to particular search (R-CNN). It likewise requires some investment to deliver every one of the pictures to prepare the model contrasted with CNN (SPPnet layer) by using Novel Pyramid Pooling Layer. The point of the research is to increase the precision of object localization by applying novel deep learning methods like the Spatial pyramid pooling net developed with deep convolutional neural network compared to Region convolutional neural network to improve accuracy.

MATERIALS AND METHODS

The work 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 Spatial Pyramid Pooling net and Region based convolutional neural network, which is used to identify objects in the image with various image datasets and labels. Group 1 is the SPPnet based R-CNN with the sample size of 10 and Group 2 is the R-CNN with sample size of 10 and it was used to compare for more accuracy score for choosing the best algorithm to detect objects correctly and quickly. A Sample size of 20 different values has been calculated with the G power having 80%, 95% confidence interval, alpha as 0.05 and beta as 0.2 values and standard deviation for SPPnet layer R-CNN = 1.39991 and R-CNN = .64140.

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.

Spatial Pyramid Pooling Net Layer Algorithm
Spatial Pyramid Pooling (SPP) places a new layer right above the fully connected network and after the primary layers. This layer moulds the input to fixed constraint pictures. The spatial pyramid match model is an old-fashioned approach in robotic vision, but in the context of CNNs and Novel Pyramid Pooling Layer is a new approach.

The SPP layer first isolates the element maps yielded from deep networks into various spatial canisters with propositions relative to the picture size, so the quantity of containers is restricted to a certain value paying little heed to the picture size. Receptacles are caught at various degrees of granularity for instance, In each spatial container, the reactions of each channel are essentially pooled utilising max pooling.

The SPP method can likewise be utilised for identification and object localization. R-CNN method is used previously, it will receive an image and iterate the image to extract the features from every window of the picture (Jiang et al. 2021). This is costly and time taking. The SPP layer utilised for object identification separates highlight maps just a single time (conceivable at numerous scales) by using a deep network and fed into deep convolutional neural networks . Then, at that point, The spatial pyramid match will apply once for every competitor window. This ends up giving equivalent outcomes, yet with running occasions 38x-102x quicker relying upon the quantity of scales.

Pseudocode
Step 1: import torch import torch.nn as nn
Step 2: from spp_layer import spatial_pyramid_pool import functools
Step 3: Def__init__(self, opt, input_nc, ndf=64, gpu_ids=[]):super(SPP_NET, self).__init__()
Step 4: Self.ouput_num → [4,2,1]
Step 5: Passing input through cnn model
Step 6: Self.conv1 → nn.conv2d(input_nc, ndf, 4, 2, 1, bias = False)
Step 7: Spp → spatial_pyramid_pool(x,1, [int(x.size(2)), int(x.size(3))], self.output_num)
Step 8: Resize and reshape the image and form a cluster pixel, Return output
Step 9: Accuracy of the Spatial Pyramid Pooling network.

R-CNN Algorithm
The second model approach is through a region based layer algorithm which is a primary and traditional approach. It works better and more efficiently than most of the traditional techniques by using these main approaches: First, it takes object proposals more over sliding windows. The R-CNN pipeline proposes a predetermined number of boxes per picture that most likely contain the required items. The proposal generation will handle the issue of different proposition scales produced by the model. The better the proposal value the better the performance of the R-CNN is determined. Second, it is trained using ImageNet Deep Convolutional Neural Network, and later trained with PASCAL VOC. But the concern about this approach is accuracy as well as process time. It is very slow compared to the primary algorithm because of the approach that uses regions to identify the items and each image individually which takes a lot of time. So based on the pre-trained model R-CNN performed little bit less than SPP (Cao et al. 2019).

Pseudocode
Step 1: import numpy, skimage.io
Step 2: Import Mask RCNN, import mrcnn.model as modellib
Step 3: Def__init__(self, opt, input_nc, ndf=64, gpu_ids=[]):super(SPP_NET, self).__init__()
Step 4: model→modellib.MaskRCNN(mode="inference",model_dir=MODEL_DIR)
Step 5: Taking image as a input
Step 6: And fed through the model → skimage(IMAGE_DIR)
Step 7: Run obtained detection outcomes → model.detect([image], verbose=1)
Step 8: results obtained will stored in an array → results[0]
Step 9: visualise the final outcomes display_instances(image,class_names, r['scores'])
Step 10: Accuracy is the output of the model.

Statistical Analysis
IBM SPSS (version 26) statistical tool is used for analysis. The sample size was calculated using a G power of 80% for each group and confidence interval of 95% for the two groups. The data collected from the iterations of a total 20 samples 10 iterations from each of the algorithms and conducted an Independent Sample T-test using SPSS statistical tool. The dependent data sets are ImageNet, PASCAL VOC 2007. The independent values are VGGNet, RetinaNet (He et al. 2015). 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 642 files on specific labels. Group statistics of SPPnet based convolutional neural network by R-CNN by grouping with iterations sample size of 10 is displayed in the Table-1, mean = 85.435 Standard Deviation = 1.39991 , Standard Error Mean = .44269.

In Table-2, The statistical analysis of two independent groups shows that the SPPnet based convolutional neural network has higher accuracy mean 85.43% and Less Loss mean 1.4170 % compared to R-CNN with accuracy 78.36% and Less Loss mean 1.7710 %.

In Table 3, The Significant value= 0.046, Mean Difference= 5.06600 and confidence interval = (4.04297 - 6.08903) of SPPnet(CNN) based Object detection and R-CNN based Object detection is displayed in Table 3. 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 SPPnet(CNN) and R-CNN Algorithms in a simple bar graph. The SPPnet(CNN) system has scored 85.43% accuracy and the R-CNN has obtained 78.36% accuracy. The SPPnet(CNN) technique has achieved better performance than R-CNN.

DISCUSSION

This work on recognizing 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 mean accuracy obtained was 85.43% using SPPnet(CNN) and 78.36% using R-CNN. And the statistical 2-tailed significance for two algorithms is 0.001 ($p<0.05$). The most important features of detecting items using “spatial pyramid pooling” layer developed with Novel Pyramid Pooling Layer (Ren et al. 2017) is pragmatically proven to be highly effective than R-CNN. The core argument is that identifying smaller items in pictures, this model may be a better method. In many of the recent findings, it has been observed that the Sppnet layer based deep network and Novel Pyramid Pooling Layer is the most focused and efficient method of recognizing items with more accuracy than R-CNN (Girshick 2015).
Localising objects implements a bounding box to pinpoint and localise every entity. As item identification is a very hot topic in computer vision, it's used in driverless vehicles (Akhtar and Mian 2018) and assistive robots (Subudhi 2009). SIFT is one of the commonly supported algorithms for object detection (“Real-Time Object Detection and Localization with SIFT-Based Clustering” 2012). and histogram of oriented gradient (HOG) (Patel et al. 2020). These approaches extract the thin prospects and scan the picture for locations with the highest class-specific response. However, these strategies are susceptible to noise and work effectively only on limited object categories. These issues restrict the applicability of standard object identification models.
The significant accomplishment of object identification (Cai and Vasconcelos 2018; Cheng et al. 2018a, b) and object localization (Lin et al. 2014) has developed under various difficulties and limitations has shown that multilayered object recognition might not be a future paradigm for quick and accurate trade off. The most common application of bound boxes is in the assessment of general object identification technique using object localisation approach and spatial pyramid pooling (Bauckhage and Tsotsos 2005), therefore this method is adopted for this research. However, as future enhancement in the scientific world progresses from picture level classification, generic object recognition and pattern identification, the future problems are predicted to the pixel level.

CONCLUSION

The objective of the work is to increase the precision of detecting objects using inventive object localisation with machine learning algorithms, SPPnet based CNN algorithm is notably better than the R-CNN algorithm. The pyramid pooling layer in SPPnet enhances the network significantly. The best algorithm from our experiment turned out to be SPPnet based neural network with higher accuracy 85.43% than the R-CNN 78.36%.

DECLARATION
Conflicts of Interest
No conflicts of interest in this manuscript.
Authors Contributions
Author MS was involved in data collection, data analysis, algorithm framing, implementation and manuscript writing. Author KM was involved in the designing the workflow, guidance and Critical review of manuscript.
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Tables And Figures

Table 1. Accuracy values of SPPnet(CNN) and R-CNN models. The SPPnet(CNN) obtained accuracy of 85.43 % compared to R-CNN having 78.36%. The significant 2-tailed value for the two groups is P = 0.001 (p<0.05).

Sample (N)	Dataset size	SPPnet (CNN)	R-CNN
1	660	85.77	79.60
2	560	84.35	78.48
3	510	84.50	77.65
4	494	84.68	76.91
5	330	86.10	76.49
6	287	86.66	78.17
7	240	86.00	77.11
8	135	86.82	79.55
9	122	86.82	79.87
10	60	83.29	78.78

Table 2. Group Statistics of spatial pyramid pooling layer based convolutional neural network by grouping with sample size 10, Mean = 85.435, Standard Deviation = 1.39991. Descriptive Statistics of the mean and standard deviation of two groups with each sample size of 10 using T-Test.

	Group	N	Mean	Std. Deviation	Std.Error Mean
Accuracy	SPPnet	10	85.435	1.39991	0.44269
	RCNN	10	78.369	0.6414	0.20283

Table 3. Independent Sample T-Test is applied for the dataset fixing confidence as 95% and level of significance as P = 0.001 (p<0.05).

<table>
<tr><th></th><th colspan="2">Levene's test for equality of variances</th><th colspan="7">t-test for Equality of Means</th></tr>
<tr><th rowspan="2">Accuracy</th><th rowspan="2">F</th><th rowspan="2">Sig.</th><th rowspan="2">t</th><th rowspan="2">df</th><th rowspan="2">Sig.(2-tailed) p</th><th rowspan="2">Mean Difference</th><th rowspan="2">Std. Error Difference</th><th colspan="2">95% confidence interval of the difference</th></tr>
<tr><th>Lower</th><th>Upper</th></tr>
<tr><td>Equal variances assumed</td><td>4.6</td><td>0.046</td><td>10.404</td><td>18</td><td>0.001</td><td>5.066</td><td>0.48694</td><td>4.04297</td><td>6.08903</td></tr>
</table>

Equal variances not assumed			10.404	12.619	0.001	5.066	0.48694	4.01078	6.12122

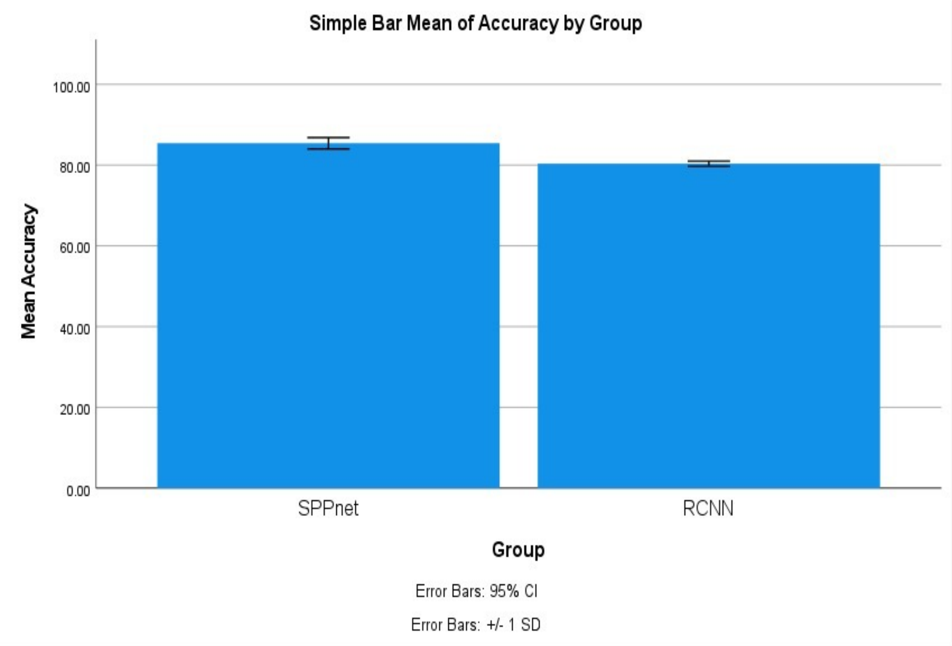

Fig. 1. Comparison of regional proposal network based SPPnet in terms of mean accuracy. As the graph shows, the mean accuracy of the SPPnet is greater than the R-CNN. Graphical representation of the bar graph is plotted using group id as X-axis SPPnet vs R-CNN, Y-axis displaying the error bars with mean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