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OBJECT DETECTION AND RECOGNITION OF SCENE IMAGES USING FR-CNN AND KERAS CLASSIFIER

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ABSTRACT
These instructions give you guidelines for preparing papers for the Journals of The World Academy of Research in Science and Engineering. Use this document as a template if you are using Microsoft Word 6.0 or later. Otherwise, use this document as an instruction set. Define all symbols used in the abstract. Do not cite references in the abstract. Due to object detection's close relationship with video analysis and image understanding, much research attention has been paid to deep learning-based object detection frameworks in recent years. These frameworks behave differently in network architecture, training strategy and optimization function, etc.A top-down tree structure is used to represent the significance of part elements of a scene image with the effort of data processing. The proposed representation is trained using a network called LSTM (Long Short-Term Memory) network.

KEY WORDS: Object Detection, Deep Learning, SVM, Neural Networks.

1. INTRODUCTION

The Windows operating system changed the way software and hardware image processing systems were created, and most developers switched to solving the problems of image processing itself. However, the progress in solving typical tasks of recognizing faces, car numbers, road signs, analysing remote and medical images, etc. is still slow.[1-5]

To gain a complete understanding of an image, we should not only concentrate on classifying different images, but also try to precisely estimate the concepts and locations of objects contained in each image. This task is called object detection.
Humans can detect and identify objects present in an image with little conscious thought. Computers can now easily detect and classify multiple objects within an image with high accuracy.[6-9]

Object recognition is a collection of related computer vision tasks that involve activities like identifying objects in digital photographs. It may be difficult for beginners to distinguish between different related computer vision tasks, especially object localization and object detection.

Object recognition refers to identifying objects in digital photographs. Region-based Convolutional Neural Networks and You Only Look Once are two families of techniques.[10-13]

Traditional object detection models can be divided into three stages: informative region selection, feature extraction and classification. SIFT, HOG and Haar-like features are representative ones, and a Supported Vector Machine (SVM), AdaBoost (Ada) and Deformable Part-based Model (DPM) are good choices for classifiers.[14-17]

State of the art results were obtained using discriminant local feature descriptors and shallow learnable architectures, but small gains were obtained using ensemble systems and minor variants of successful methods.[18-20]

Deep Neural Networks (DNNs) have become more significant in object detection thanks to Regions with CNN features (R-CNN). Several improved models have been suggested, including Fast R-CNN, Faster R-CNN and YOLO.

Deep Neural Networks (DNNs) have become more significant in object detection thanks to Regions with CNN features (R-CNN). Several improved models have been suggested, including Fast R-CNN, Faster R-CNN and YOLO.[20-21]

In this paper, we review several deep learning models for object detection, including generic object detection, salient object detection, face detection, and pedestrian detection. The models are achieved using bounding box regression, local contrast enhancement, and multi-feature fusion/boosting forest.[22-26]

In this paper, CNN is used for object detection. Several specific tasks are reviewed, including salient object detection, face detection and pedestrian detection.

1.1 OVERVIEW OF DEEP LEARNING

Neural networks were popular in the 1980s and 1990s but fell out of fashion in early 2000s due to overfitting and lack of large-scale training data.

Deep learning has become popular since 2006 with a breakthrough in speech recognition. The recovery of deep learning can be attributed to the emergence of large-scale annotated training data, fast development of high-performance parallel computing systems, and significant advances in the design of network structures and training strategies.

CNN is a model for deep learning that uses a 3D matrix of pixel intensities for different color channels to represent features. Different types of transformations can be conducted on CNN feature maps, such as filtering and pooling.

An initial feature hierarchy is constructed with convolution and pooling, and the network is then fine-tuned in a supervised manner by adding several fully connected (FC) layers. It is then optimized on an objective function via the stochastic gradient descent (SGD) method.

The advantages of CNN against traditional methods can be summarised as follows: - CNNs can learn hierarchical feature representations from data automatically; - CNNs can jointly optimize several related tasks; - CNNs can solve some classical computer vision challenges from a different viewpoint.

1.2 GENERIC OBJECT DETECTION

Generic object detection methods include R-CNN, SPP-net, Fast R-CNN, Faster R-CNN, R-FCN, FPN, Mask R-CNN, MultiBox, AttentionNet, G-CNN, YOLO, SSD, YOLOv2, DSSD and DSOD.

The region proposal-based framework matches the attentional mechanism of human brain to some extent and predicts bounding boxes directly from locations of the topmost feature map.

Ross Girshick proposed R-CNN in 2014 to improve the quality of candidate bounding boxes and to extract high-level features. R-CNN uses selective search, CNN based deep feature extraction and classification and localization.

We propose a simple and scalable method for object detection that combines convolutional neural networks with region proposals, and when labelled training data is scarce, supervised pre-training for an auxiliary task, followed by domain-specific fine-tuning, yields a significant performance boost.

SIFT and HOG are block wise orientation histograms, and the performance on PASCAL VOC object detection has been slow during 2010-2012. Fukushima's "neocognitron" suggests that there might be more informative features.

The neocognitron, a hierarchical and shift-invariant model for pattern recognition, lacked a supervised training algorithm. LeCun et al. showed that stochastic gradient descent can train convolutional neural networks (CNNs), which extend the neocognitron.

R-CNN has several disadvantages, such as requiring a fixed-size input image, training is a multi-stage pipeline, and the obtained region proposals are still redundant. To solve these problems, many methods have been proposed, such as GOP, MCG, and edge boxes.

In addition to R-CNN, several improved object detectors have been proposed, such as Zhang et al. 's Bayesian optimization-based search algorithm, Saurabh Gupta 's geocentric embedding for depth images, and Ouyang 's deformable deep CNN (DeepID-Net).

2. LITERATURE REVIEW

Object detection is an important topic of research. We compiled information on various object detection tools and algorithms used by different researchers.[27]
Ross Girshick has introduced the Fast R-CNN model, which makes use of the CNN method in the target detection field. It is nine times faster than the R-CNN model.[28]

Another research work done by Kim et al is discussed here. This research work uses CNN with background subtraction to build a framework that detects and recognizes moving objects using CCTV cameras. It is based on the application of the background subtraction algorithm applied to each frame.[29]

Joseph Redmon et al proposed You Only Look Once (YOLO), a one-time convolutional neural network for the prediction of the frame position and classification of multiple candidates. Tanvir Ahmed et al proposed a modified YOLO v1 network model.[30]

Wei Liu et al developed a method for detecting objects in images using a single deep neural network. This method eliminates the process of generating a proposal and eliminates the subsequent pixel and resampling stages.[31]

A paper on Tiny SSD, a single shot detection deep convolutional neural network, is based on an advanced type of SSD. The paper uses a 2.3 MB small network and achieves the best results in embedded detections.[32]

ResNet is a powerful backbone model used in many computer vision tasks. It allows training extremely deep neural networks.

Selective Search is a region proposal algorithm that groups pixels based on their pixel intensities, and then uses a convolutional neural network to extract features from the image. The features are then fed into an SVM to classify the presence of an object within the region proposal.

R-CNN can be implemented in real time, but it takes 47 seconds per test image and no learning happens at that stage.
Fast RCNN is a faster object detection algorithm based on R-CNN. It uses a convolutional feature map instead of region proposals and a SoftMax layer to predict the class of the proposed region.

Fast R-CNN aggregates CNN features from different regions of interest in a single forward pass.
A region proposal network (RPN) is a fully convolutional network that generates proposals with various scales and aspect ratios. It uses the terminology of neural network to tell the object detection where to look.

YOLO is an object detection algorithm that only looks at parts of the image and predicts the bounding boxes and class probabilities for these boxes.

The YOLO algorithm works by splitting an image into a grid and taking m bounding boxes for each grid. The bounding boxes with the highest-class probability are used to locate the object within the image.
Some disadvantages of YOLO Based Convolutional Neural Networks, Fast R-CNNs, and YOLO (You Look Only Once)
The SSD object detection uses VGG16 to extract feature maps, and the Conv4_3 layer to detect objects.

Conv4_3 makes 38 predictions per cell and picks the highest score for each class.
SSD resolves to a very simple method by using convolution filters. It gives 21 scores for each class plus one boundary box.
SSD uses multiple layers for detecting objects independently and uses lower resolution layers for detecting larger-scale objects.

3. PROPOSED SYSTEM

The LSTM network is trained using images from datasets and parsed tree representations. The accuracy of the object detection method is influenced by the image composition and the discovered parts.

The object detection may not be agnostic to the entire content of the image due to being influenced by the image composition and the discovered parts. The attempt has been made to show the object detection as a representation of the objects and their locations, parts of these objects, and the accuracy of the object detection method has been noted to have an efficient record with the implementation of the baseline Fast Region Based Convolutional Neural Network (FR- CNN) method. More efficient than existing methods.

3.1 METHODOLOGY

Our model uses FR-CNN for object detection and an image classifier for object classification. The output is displayed as label of the object detected from the image with confidence score.

Object recognition involves identifying objects in digital photographs. Image classification and object localization involve predicting the type or class of an object in an image, and object detection involves localizing and classifying one or more objects in an image.
Object detection is the process of locating objects in an image.
Computer vision tasks include object recognition, object instance segmentation, and semantic segmentation.

3.1.1 DATA COLLECTION

Data collection is the process of gathering information in digitized form. There are different types of data collection and different tools, and techniques exist.
Data collection is the process of gathering, measuring, and analysing accurate data from a variety of relevant sources to answer research questions, ensure quality assurance, and keep research integrity.
Researchers must answer three questions before beginning data collection. They must also identify the data types, sources, and methods being used.
Data collection can be done using a telephone survey, a mail-in comment card, or even by asking passers-by some questions.
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Interviews are the most common means of data gathering, followed by the projective technique, the Delphi technique, and focus groups. Questionnaires are another common method of data gathering.

For secondary data collection, the researcher consults various data sources, such as financial statements, sales reports, retailer/distributor/deal feedback, and customer personal information.

There are many different types of interviews, and each type is broken down into specific tools. For example, word association, sentence completion, role-playing, online/web surveys, mobile surveys, phone surveys are some of the different types of interviews.

When collecting data for training the ML model, it is important to ensure that the data is accurate, that no sub-data is missing, and that there are no biases in the data.

Several techniques can be applied to address problems of image classification and object recognition, including pre-cleaned, freely available datasets, web crawling and scraping, private data, and custom data.

Table 1: Fruits and Vegetables set.

Classes:	Fruits	Vegetables
Sub-Classes:	• Apple • Orange • Mango • Dates • Strawberry • Grapes • Cherry • Banana • Sapodilla • Lemon • Coconut • Pomegranate • Blue berry • Pears • Mosambi	• Onion • Carrot • Beans • Potato • Brinjal • Chilli • Okra • Ginger • Garlic • Bitter guard • Cauliflower • Tomato • Beetroot • Capsicum • Corn

3.1.2 DATA PRE-PROCESSING

Data pre-processing transforms raw data to be used in machine learning and AI. It is done at the earliest stages of the pipeline to ensure accurate results.

Before you feed your images to the ML model, you must process them to make them the same size.

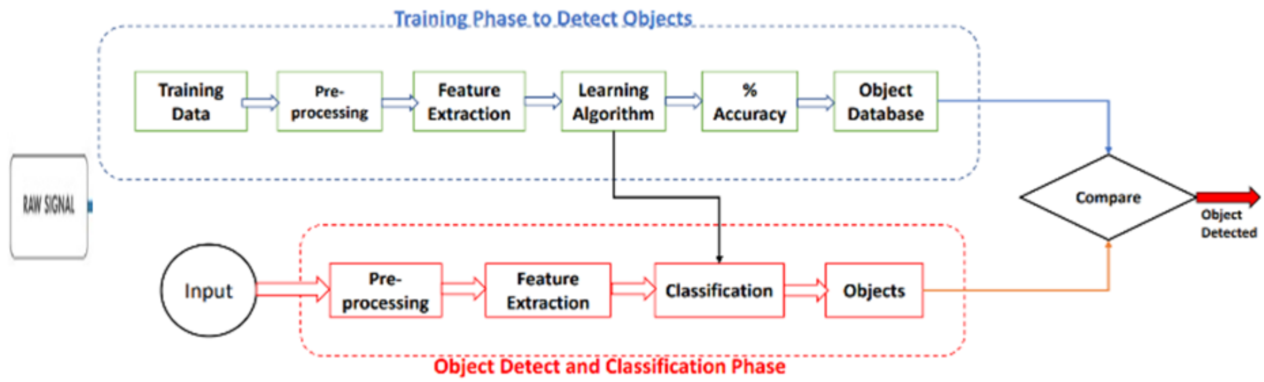

Figure: 1- Pre-Processing.

The acquired data need to be cleaned up and standardized before feeding them to the machine learning model. Several techniques are used for data cleaning and pre-processing, including data cleaning, data imputation, data normalization, data integration, and data integration with other datasets.

```
Out[63]: array([[[[0.78431374, 0.72156864, 0.65882355],
                  [0.78431374, 0.7176471 , 0.6666667 ],
                  [0.78039217, 0.7137255 , 0.6627451 ],
                  ...,
                  [0.7647059 , 0.7411765 , 0.627451  ],
                  [0.75686276, 0.7372549 , 0.6156863 ],
                  [0.7529412 , 0.73333335, 0.6039216 ]],

                 [[0.7921569 , 0.7294118 , 0.6666667 ],
                  [0.7882353 , 0.72156864, 0.67058825],
                  [0.78039217, 0.7137255 , 0.6627451 ],
                  ...,
                  [0.7647059 , 0.7411765 , 0.627451  ],
                  [0.7490196 , 0.7294118 , 0.60784316],
                  [0.7490196 , 0.7294118 , 0.6       ]],

                 [[0.79607844, 0.73333335, 0.67058825],
                  [0.7921569 , 0.7254902 , 0.6745098 ],
                  [0.78039217, 0.7137255 , 0.6627451 ],
                  ...,
                  [0.7529412 , 0.7294118 , 0.6156863 ],
                  [0.7490196 , 0.7294118 , 0.60784316],
                  [0.7372549 , 0.7176471 , 0.5882353 ]],

                 ...,

                 [[0.72156864, 0.69803923, 0.7176471 ],
                  [0.73333335, 0.70980394, 0.7294118 ],
                  [0.72156864, 0.69803923, 0.72156864],
                  ...,
                  [0.23529412, 0.23921569, 0.22352941],
                  [0.23921569, 0.24313726, 0.22745098],
                  [0.21960784, 0.22745098, 0.20784314]],

                 [[0.7294118 , 0.69803923, 0.7137255 ],
                  [0.7411765 , 0.7058824 , 0.72156864],
                  [0.7411765 , 0.7058824 , 0.7137255 ],
                  ...,
                  [0.23529412, 0.23921569, 0.22352941],
```

Figure: 2- Pre-Processing Matrix.

3.1.3 FEATURE EXTRACTION

Feature extraction is the process of transforming raw data into numerical features that can be used in machine learning algorithms.

Feature extraction for image data is accomplished using specialized algorithms. Deep learning can skip the feature extraction step, but still requires effective representation of image features.

Figure: 3- Feature Extraction.

3.1.4 TRAINING

The RPN uses two different types of predictions: the binary classification and the bounding box regression adjustment. It uses a mini batch of 256 anchors and uses Smooth L1 loss to reduce the loss in the regression adjustment.

Using dynamic batches can be challenging because of the imbalance between background and foreground anchors. We use the anchors with the biggest IoU to the ground truth boxes.

After putting the complete model together, we have 4 different losses, two for the RPN and two for R-CNN. We can train the base network or not, depending on the nature of the objects we want to learn.

The four different losses are combined using a weighted sum, and depending on the base network being used, regularization losses may also be used. We train using Stochastic Gradient Descent with momentum.

Figure: 4- Training Model.

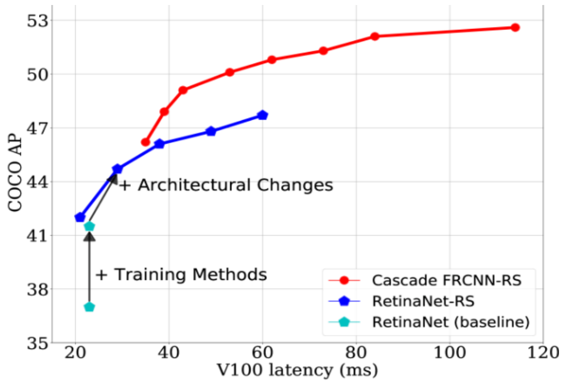

Figure: 5- Training Accuracy Graph.

4. TESTING

To avoid duplicate proposals, we use a simple algorithmic approach called Non-Maximum Suppression (NMS). The threshold for IoU is important, as too low a threshold may miss proposals.

The bounding box adjustments need to be applied to the proposals with the highest probability.

We apply class-based NMS to get the final objects. We also set a probability threshold and a limit on each class.

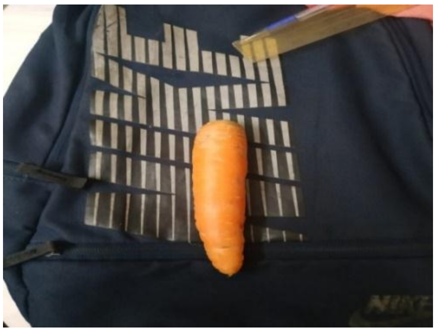

Figure: 6: Testing Input.

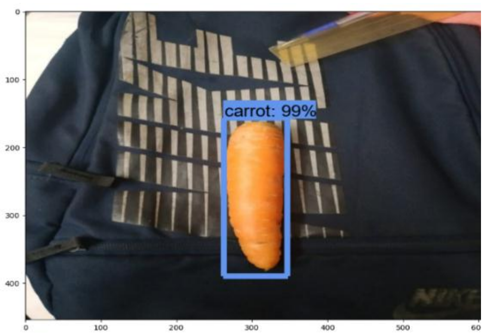

Figure: 7: Tested Output.

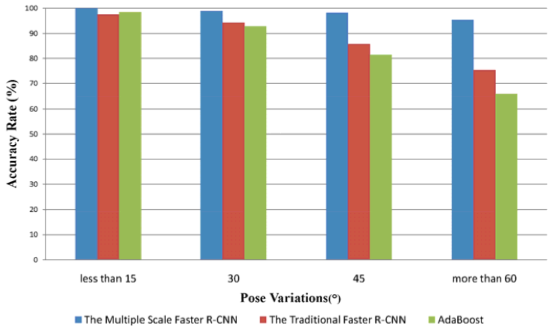

Figure: 8- Testing Accuracy Graph.

5. RESULTS AND DISCUSSION

An image is given as input to our model, and it is detected using FR-CNN and then the detected image is classified using an image classifier.

utput is displayed as label of the object detected from the image with confidence score.

The two main phenomena happening in our model is Object detection and Object classification.

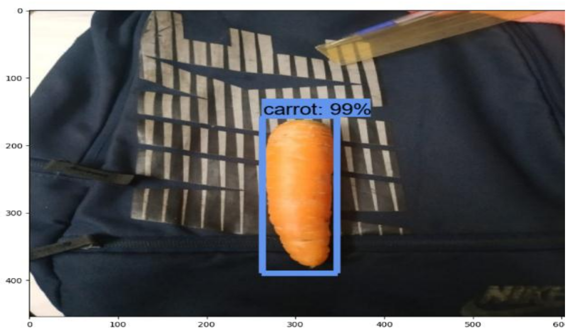

Figure: 9- Output.

R-FCN and SSD models are faster on average but cannot beat the Faster R-CNN in accuracy if speed is not a concern. Faster R-CNN requires at least 100 ms per image. Use only low-resolution feature maps for detections hurts accuracy badly. Choice of feature extractors impacts detection accuracy for Faster R-CNN and R-FCN but less reliant for SSD.

Input image resolutions and feature extractors impact speed. Below is the highest and lowest FPS reported by the corresponding papers. Yet, the result below can be highly biased they are measured at different mAP.

FPN and Faster R-CNN (using ResNet as the feature extractor) have the highest accuracy. RetinaNet builds on top of the FPN using ResNet. So, the high mAP achieved by RetinaNet is the combined effect of pyramid features, the feature extractor's complexity and the focal loss. Yet, you are warned that this is not an apple-to-apple comparison. We will present the Google survey later for better comparison. But it will be nice to view everyone claims first.

6. CONCLUSION

By using this thesis, we are able to detect objects more precisely and identify the objects individually with exact location of an object in the picture in x,y axis. We also compare different methods for object detection and identification and identify the limitation of each method.

In this project, review on different object detection, tracking, recognition techniques, feature descriptors and segmentation method which is based on the video frame and various tracking technologies. This approach used towards increase the object detection with new ideas. Furthermore, tracking the object from the video frames with theoretical explanation is provided in bibliography content.

Also, we have noted some methods which give accuracy but have high computational complexity. Specifically, the statistical methods, background subtraction, temporal differencing with the optical flow was discussed. However, these technique needs to concentrate towards handling sudden illumination changes, darker shadows, and object occlusions

FUTURE ENHANCEMENT

More datasets can be added compare to the original data. The object recognition system can be applied in the area of surveillance system, face recognition, fault detection, character recognition etc. The objective of this thesis is to develop an object recognition system to recognize the 2D and 3D objects in the image. Detecting objects from multiple image inputs. Addition of User Interface for enhanced user experience can be done in future enhancements.

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