

Final Report

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| School of Computing  Faculty of Engineering AND PHYSICAL SCIENCES |

<Object Detection Website Based on Deep Learning>

<Yunjia Feng>

Submitted in accordance with the requirements for the degree of  
<BSc Computer Science>

**<2021/22>**

The candidate confirms that the following have been submitted*:*

*<As an example>*

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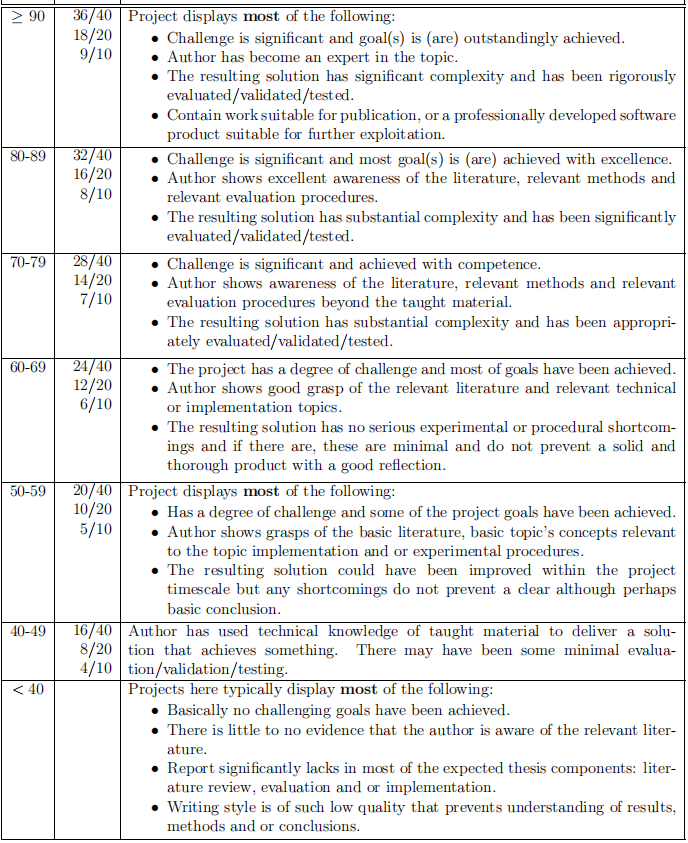
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# Summary

*<Concise statement of the problem you intended to solve and main achievements (no more than one A4 page)>*



# Acknowledgements

*<This page should contain any acknowledgements to those who have assisted with your work. Where you have worked as part of a team, you should, where appropriate, reference to any contribution made by others to the project.>*

*Note that it is not acceptable to solicit assistance on ‘proof reading’ which is defined as “the systematic checking and identification of errors in spelling, punctuation, grammar and sentence construction, formatting and layout in the text”; see*

https:://www.leeds.ac.uk/secretariat/documents/proof\_reading\_policy.pdf

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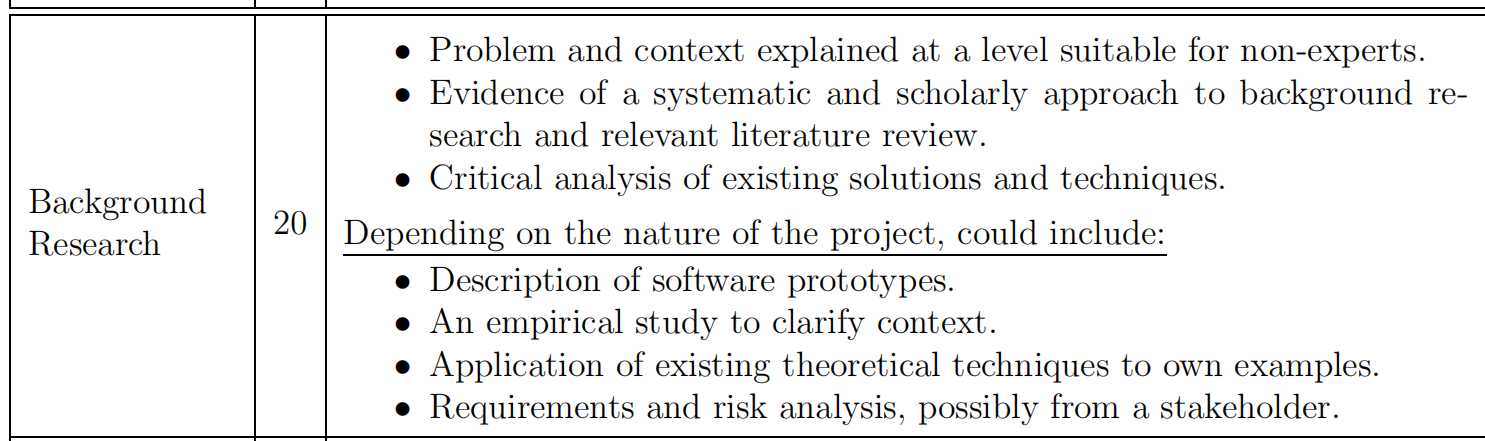
# Chapter 1 Introduction and Background Research

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Problem and Context

Analysis of existing solutions and techiniques

Description of software prototypes,



## 1.1 Introduction

<A brief introduction suitable for a non-specialist, *i.e.* without using technical terms or jargon, as far as possible. This may be similar/the same as that in the 'Outline and Plan' document. The remainder of this chapter will normally cover everything to be assessed under the `Background Research` criterion in the mark scheme.>

Computer vision analysis of target motion can be roughly divided into three levels: motion segmentation and object detection, target tracking, action recognition and behavior description[2].Object detection has always been of great significance in the field of computer science, with the main objective to enable the computer to accurately classify the objects in a given picture and find the position of each object. Object detection is not only one of the basic tasks to be solved in the field of computer vision but also the basis of video surveillance technology among the other tasks. However, object detection is still a challenging task with great potential and has great space for improvement, since the objects in the video have different poses and often appear to overlap, especially when their movements are irregular. Meanwhile, the resolution, weather, illumination, and other conditions of the surveillance video or images as well as the diversity of scenes should also be taken into consideration, which makes this task more challenging.

In recent years, many computer vision researchers both at home and abroad had developed a large number of excellent object detection algorithms in a neural network, including Faster R-CNN, SSD, YOLO.

From the perspective of research, the significance of object detection dues to it is one of the fundamental tasks in the field of computer vision, since it is the basis of many other high-level tasks, including image classification, face recognition, target tracking, pedestrian re-recognition. Meanwhile, there is a large number of well-known national and international research teams had been focused on the field of object detection: MIT Computer Science and Artificial Intelligence Laboratory, Stanford Computer Vision Lab, National Laboratory of Pattern Recognition of Chinese Academy of Sciences, LAMDA Institute of Nanjing University.

While from the perspective of the application, object detection has shown a wide range of practical usages: face detection technology, pedestrian detection technology applied in video surveillance, entrance and exit statistics, traffic sign detection technology, vehicle detection technology applied in aided driving, automatic driving. At the same time, major technology companies, for example, Microsoft, Google, Ali, and Baidu, have also spent a lot of manpower and material resources to explore the object detection field, which also indicates the significance and prospect of object detection.

The goal of this project is to select appropriate object detection algorithms and data sets to train a deep learning model, then develop a website for users which allows them to complete object detection tasks easily. Moreover, the website should provide additional functions that exclude basic object detection functionality to offer users a better experience, for instance, allowing them to change weights to suit different tasks, or mark recognition results after logging in.

## 1.2 Literature Review

<This section heading is purely a suggestion -- you should subdivide this chapter in whatever manner you think makes most sense for your project. It may also make sense to spread the `Background Research' over more than one chapter, in which case they should be named sensibly.>

Object detection had long been one of the most important and challenging task in computer vision, which detects instances of objects in a given image. It is also basis of other high-level significant computer vision tasks, instance segmentation[1-4], object tracking[8], etc.

Over twenty years, object detection had been developed rapidly especially due to the archivement of deep learning recently[9], tremendous imrpovements pushed many applications into usage, for instance, face detection technology, autonomous driving, pedestrian detection technology applied in video surveillance, entrance and exit statistics.

Looking back through the history of object detection, it could be divided into two periods: traditional method and deep learning method with the separate line of 2014.

In general, object detection is a task to find all the objects of interest in the image for two sub-tasks, including object positioning and object classification[3]. The traditional object detection method, for example, the sliding window algorithm is generally divided into three stages: firstly, select some candidate regions on a given image, then extract features from these regions, and finally classify them using trained classifiers.

Traditional methods also include Viola Jones Detectors (2001)[10,11], HOG Detector(2005)[12] and DPM (2008). DPM, stands for Deformable Part-based Model, was the winner of the VOC-2007 competition, which also was the best technique in the end era of the traditional method, which focusing on detecting smaller parts of an object, for example, a human could be divided into arms, legs, head.

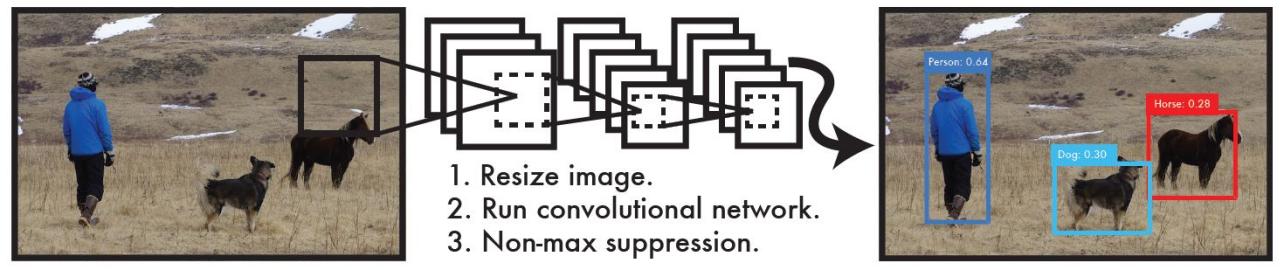
The efforts of traditional methods not only clear the path but also brought many inspirations to the researchers who study deep learning methods.

Since 2006, in the lead of Hinton, Bengio, Lecun, and other researchers, an enormous number of deep neural network papers had been published, especially after Hinton's research group participated in the ImageNet image recognition competition in 2012 and won the championship using AlexNet[1], constructed by CNN (Convolutional Neural Network), then neural networks began to receive extensive attention from then on.

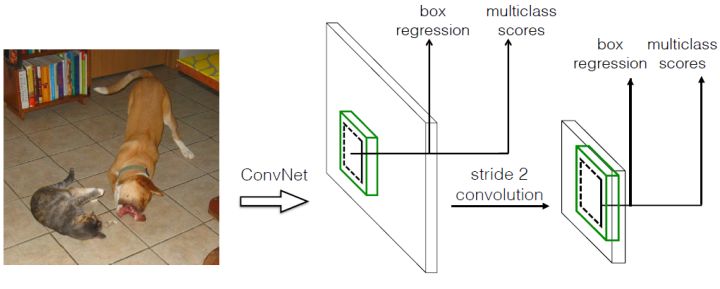
In the deep learning era, the methods were normally divided into two categories: one-stage methods and two-stage methods:

* One-stage object detection algorithms hold the philosophy of detect the objects in only one step. This kind of detection algorithm does not need the Region Proposal Stage and can directly generate the category probability and position coordinates of objects through only one stage. One-stage typical algorithms include YOLO, SSD, RetinaNet and CornerNet[4].
* Two-stage object detection algorithms embrace the idea of “from coarse to fine”[正序15], they divide detection problems into two stages, the first stage is the generation of Region Proposals, which includes the approximate location information of the object, and the second stage is the classification and location refinement of the candidate regions. The representatives of two-stages algorithms are R-CNN, Fast R-CNN, Faster R-CNN, etc.

YOLO stands for “You Only Look Once”, is one of the most famous and first one-stage object detection algorithm, adopts a separate CNN model to achieve end-to-end object detection.. YOLO-v0 originates from the idea of trasnforming the classificationing network directly into positioning network by dividing the image into serveral parts, then predicts with bounding boxes. In general, the input image is resized and sent to the CNN network, then the detected object results are obtained by processing network prediction. Compared with the R-CNN algorithm, YOLO is a unified framework with faster speed while the training process is also end-to-end[11]. Since YOLO both has rapid recognition speed and high accuracy, which is suitable for a lightweight website application, this project adopts YOLO-v5 as basis to develop a object detection website. More details will be concentrated on YOLO from v0 to v5 in later chapters.



**Figure 1.2.3** YOLO basic structure

SSD [21] stands for Single Shot MultiBox Detector, is a single-stage, multiple proposal object detection algorithm. The uniqueness of SSD is its multi-scale detection techiniques which allow predicting different sizes of objects using different layers in the network, which significantly enhance the accuracy of single stage method. SSD also uses CNN with a multi-scale feature map to detect objects, the basic structure shows as the figure below:

**Figure 1.2.1** SSD basic structure

Additionally, SSD adopts VGG16 as the basic model, and then adds a convolution layer based on VGG16 to obtain more feature maps for detection[5]. There are also some improved algorithms based on SSD, for instance, DSSD[6] and FSSD[7], which have a different structure for their CNN module.

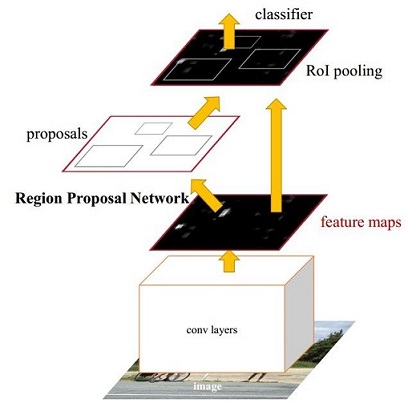
RetinaNet was proposed in 2017[23], which deeply analyse the differences between one-stage methods and two-stage methods, and designed a new loss fucntion called “Focal Loss” in order to solve the problem of imblanced data.

R-CNN, Fast R-CNN, and Faster R-CNN are a series two-stage algorithms. R-CNN introduces selective search to generate 2000 proposals, then resizes them to fed in a CNN network for feature extraction, a SVM classifier will handle the features and give predictions.[正序8]

Since the 2000 proposals of R-CNN needs large computational resources, leading a really slow speed, Fast R-CNN extracts features from the whole image instead of proposal regions to update weights, and adopts selective search to the outputs of convolution rather than raw image which signifiticantly reduces computation cost and enhance detecting speed.[24]

The Faster R-CNN

Faster R-CNN, is a model after the evolvement of R-CNN and Fast R-CNN, when Ross B. Girshick proposed it in 2016[8]. It adopts RPN (Region Proposal Network) to replace original selective search, reducing a large mount of computation redundancy and improve accuracy at the same time.[正序9] In terms of structure, the Faster R-CNN integrated feature extraction, bounding box regression (rectangular refine), and classification into one network, which greatly improves the overall performance[9], especially in the detection speed. The structure of the network is shown as below:



**Figure 1.2.2** Faster R-CNN basic structure

Furthermore, Cascade R-CNN was proposed as a multiple-stage method on the basis of previous versions[10] but has better accuracy in detection.

Excellent algorithms still need proper dataset to train ane evolve, competitions normally will be hold to test performance on datasets for famous algorithms, also serving as benchmark for later research. Among these datasets, Pascal VOC, MS-COCO and Open Images are frequently used for object detection tasks.

Pascal VOC stands for The PASCAL Visual Object Classes (VOC) Challenges[50,51], supports many computer vision tasks, for example, object detection, instance segmentation, [放图 link] object tracking. Since Pascal VOC is one of the most important dataset for object detection, so there are already benchmarks created by other famous algorithms. Moreover, with relatively smaller size than others, Pascal VOC is suitable for this lightweight project. This project finally selects VOC 2007 for training, because VOC 2007 focused on object detection tasks, but the latter version (VOC 2012) also used for other tasks (instance segmentation and object tracking). Despite its small size, it also has enough data to train a decent model, with 9963 images (train, validation and test), in total 24640 objects for 20 different classes.

MS-COCO is also a famous dataset that used in object detection task, which has more than 160 thousand images with about 900 thousand objects for 80 classes. Open Image dataset is normally used in two tasks: object detection and predict relationships between objects.

Within the appropriate algorithm and datasets for training, then a evaluation metrix is needed to test the performance of a method. In object detection task, mAP (mean Average Precision) is one of the most important indicator, which was first mentioned in VOC-2007. To define AP, PR (Precision-Recall) curve is requested with specified IoU (Intersection over Union) threshould (usually 0.5), the area under the PR curve means the AP value. After that, sum up all the AP for every class then divide class number can obtain the final mAP.

Among the history of object detection, there are some important concepts that brought huge influence to current object detection research need to be mententioned.

CNN, stands for convolutional neural networks, had been used since 1990[96 ?是否引用] in a variety of computer vision field. CNN had began the new era of deep learning by allowing parameter sharing and sparsity of connections, which serve as the basis of all the one-stage and two-stage methods that mentioned above.

NMS, stands for Non-Maximum Suppression, is a technique that used to eliminate redundant bounding boxes for the same object generated by the network. There are also many other NMS versions, for instance, Soft-NMS, DIoU NMS, Conv NMS, Learning NMS, etc. The invention of NMS had greatly enhanced accuracy of the algorithms, which make it remains necessary component of modern network.

Moreover, some new strategies that used to applied in other filed are now put into experiment in object detection and yield remarkable results.

Adversarial training, or GAN (Generative Adversarial Networks) [286] is quite popular these days especially in researches that allowing AI to generate their own production (composing songs, draw paintings, etc.). Typically, GAN includes two networks, one “teacher” network to criticise the AI production, while another one “student” network generate AI production, two networks will learn together and yields better results after training. For object detection task, GAN had been put into usage to enhance the performance when detecting small or overlapping objects.

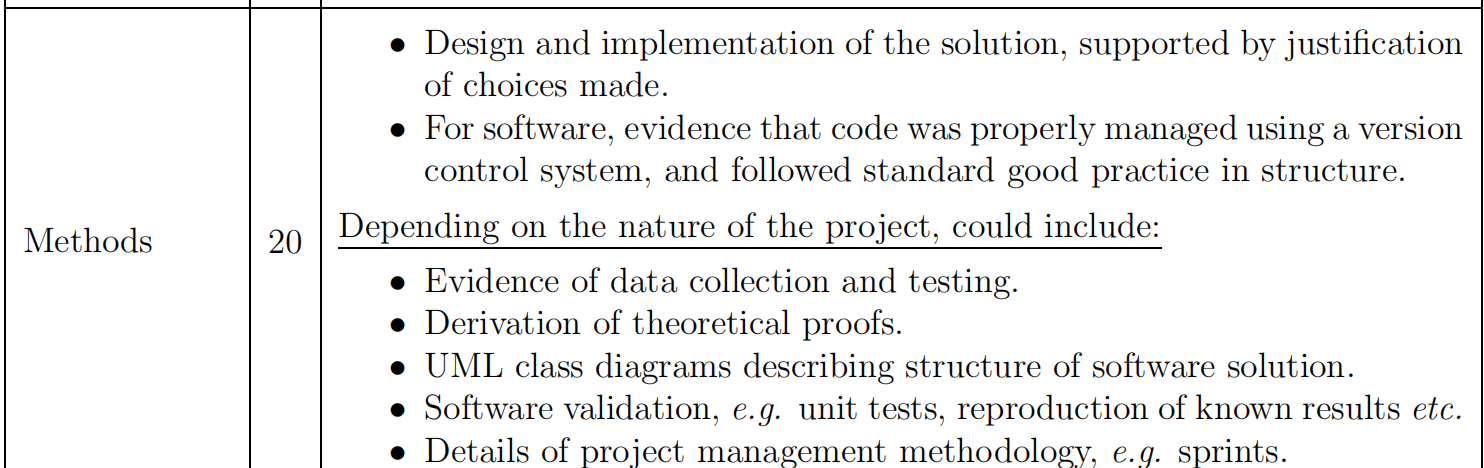
Inspite of the great progress that object detection ever had since start, there are still some serious challenges that had troubled many researchers till now, for instance, when detecting bad weather situation (strongly snowy, foggy, etc.), or many small targets overlapping (a really busy street with hundreds of pedestrians) performance of algorithms normally are [barely](javascript:;) [satisfactory](javascript:;). To solve these problems above, further researches are needed to enable object detection techniques to applied in more situations to provide people better lives. For the future, object detection researches may focued mroe on real-time techniques, which could provide video surveillance on road or autonomous cars. Therefore, video instead of images would become the mainstream media to apply object detection, which means more fast but accurate algorithms will be developed to serve the needs. Object detection application that in smartphones is also a promising direction, which may also trigger the development of more light-weight models that could used in mobile devices. It is reasonable to believed that in the future, object detection techniques will be more important in people’s lives than ever.

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测试

# Chapter 2 Methods

<Everything that comes under the `Methods' criterion in the mark scheme should be described in one, or possibly more than one, chapter(s). Note that it is not normally relevant to include extensive code, but short snippets for key aspects may be suitable.>



Justification of choices made

Version control system evidence,

good practice in structure

Data collection(format transform, VOC2007), testing(Postman, Selenium, pytest...)

UML class diagrams describing structure of software solution

Software validation (unit tests, reproduction fo known results)

Details of project managemnet methodology (sprints) ? Agile???

## 2.1 Table example

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| **Heading One** | **Heading Two** | **Heading Three** |
| 1.1 | 1.2 | 1.3 |
| 1.21 | 1.22 | 12.3 |
| 12.31 | 12.32 | 12.33 |

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## 2.2 Figure example

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**Figure 2.1** This is the figure description in the ‘figure description’ style.

The traditional method -- sliding window algorithm use different sizes of boxes to go through the image step by step. However, this method has a serious drawback: to obtain higher accuracy, the stride of the boxes need to be smaller, which needs incredibly huge amout of computational resource and costs a long time. Moreover, two potential problems exist in this method:

* Different sizes of boxes means different sizes of inputs. Thus, normalization process need to be added int the network.
* Since the method will brute forcely go through the whole image, the background areas must larger than the object areas, which will cause imbalanced data (imblance between positive and negative samples).

To solve the problem above, the origin of YOLO-~~v0~~ is designed by simply transforming a classification detector into an object detector that could predict objects locations. The traditional classification network normally ends with a fully-connected layer outputs N dimentional ont-hot vector, so the author of YOLO just change the output layer into an another vector (x,y,w,h,c) (x and y denotes the coordinates location of the top-left location of the bounding box, w and h means the width and height the bounding box, c is the confidence of the object), forming a object detector.

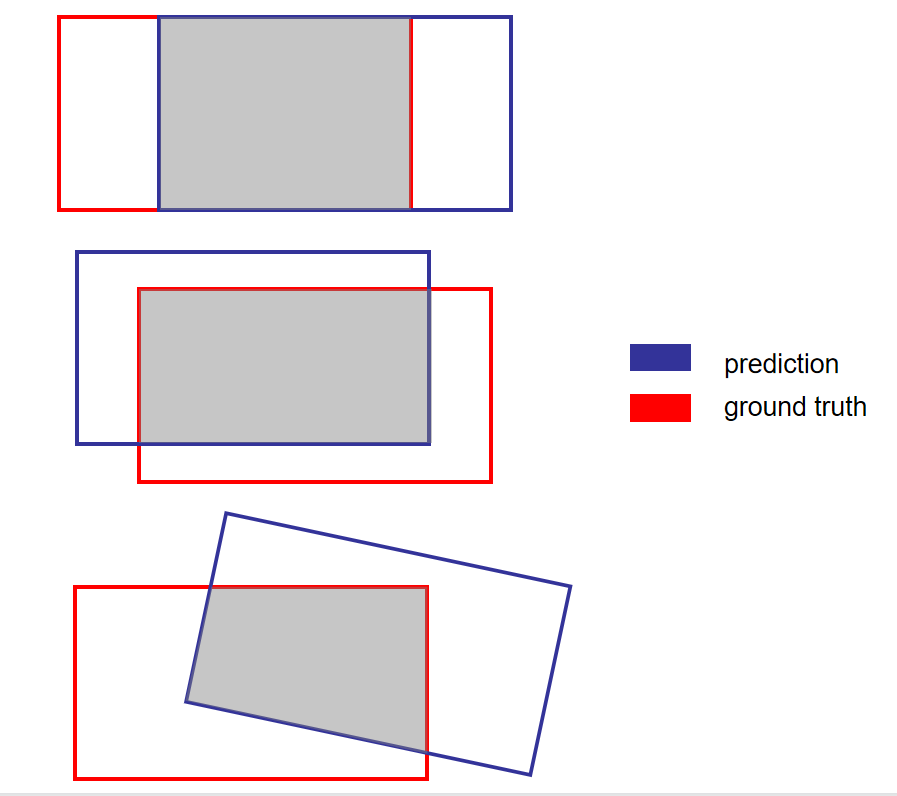
From the description above, YOLO-v0 can only output one object for one image, in order to detect multiple objects in one image, YOLO-v1 was deviced. First of all, instead of output only one set of ont-hot vector (x,y,w,h,c), the network divided the image into 7\*7 intotal 49 regions, one region is corresponding for one set one-hot vector output. Moreover, if one object spanned more than one regions, NMS is used to select the most confident region and give out prediction. If there are multiple classes, YOLO-v1 just simply increase the output, and repeat the 7\*7 region detect for each class. To solve the problem of detecting small objects, YOLO-v1 specifically add extra neureon network layers to handle them, which means there are two sets of one-hot vector (in total 98 bounding boxes), one for big targets while the other handling small objects. For the other components, YOLO-v1 takes GoogleNet as the backbone without neck, which belongs to dense prediction detector. For training, YOLO-v1 trains the classification network with 224\*224 resolution rate, then trains the detection network with 448\*448 resolution rate.

Nevertheless, YOLO-v1 still had some problems left unsolved. Despite the fast speed, the accuracy of the network is not satisfying, and the recall is relatively low which means many targets are missing.

To tackle the first problem, YOLO-v2 used anchor box for width and height, which was first introduced in R-CNN, aiming predict relative offsets instead absolute offsets. Because the offset after regularization is smaller than the original height and weight values, the network can learn better and provide better accuracy. For the second problem, YOLO-v2 evlove the network strcuture from 7\*7 to 13\*13 to promote recall, with maximum 169 objects could be detected. Even though YOLO-v2 still does not have a neck component, the backbone is switched to darknet-19, and fully-connect layer is subsititued by GAP (Global Average Pooling) layer to enhance the accuracy for small objects. The training process for YOLO-v2 is also much more complicated: first of all, Darknet-19 is pre-trained in the ImageNet classification dataset for 160 epoches with 224\*224 resolution rate, then they finetune the classification model for 10 more epoches with 448\*448 resolution rate, since the usage of GAP allow training could accept different size of inputs.

Even though YOLO-v1 added an extra output layer to detect small objects, the result was still not promising. The author of YOLO noticed this and changed CNN downsampled rate into three branches: 32x-down sampling, 16x-down sampling, and 8x-down sampling, respectively detects for big, medium and small objects, in total generate 10467 bounding boxes, way larger than YOLO-v2 845 bounding boxes. YOLO-v3 also uses FPN as the neck, which could pass the feature information from bottom layer to upper layer, For the other components, YOLO-v3 updates the backbone to Darknet-53 with the introduction of Resnet, which makes the network deeper, contributes a lot for higher accuracy.

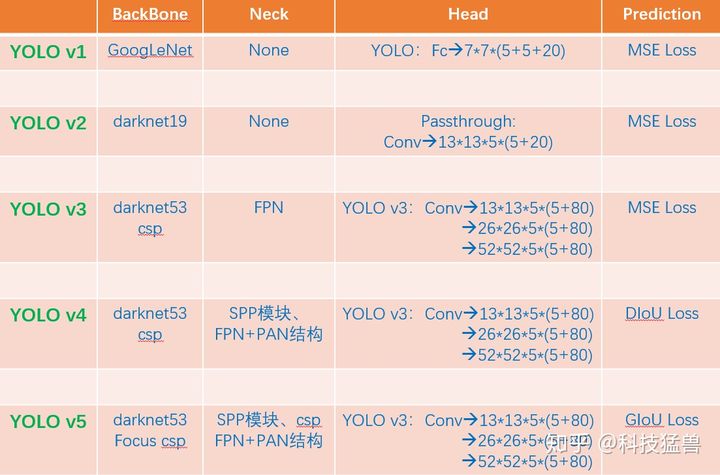
YOLO-v4 improved the head of the network by using multiple anchors to predict single ground truth, which could increase the number of positive samples, aiming at mitigate the problem of imbalance between the positive and netgative samples. Moreover, from v0 to v3, YOLO adopts the traditional MSE (Mean Squared Error) loss when calculating loss function, but MSE loss can not tell the difference overlapping area or IOU are the same.

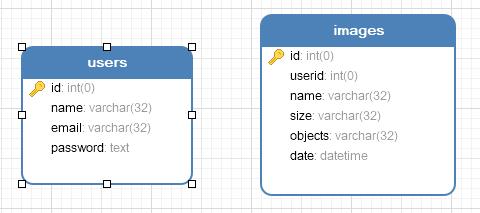


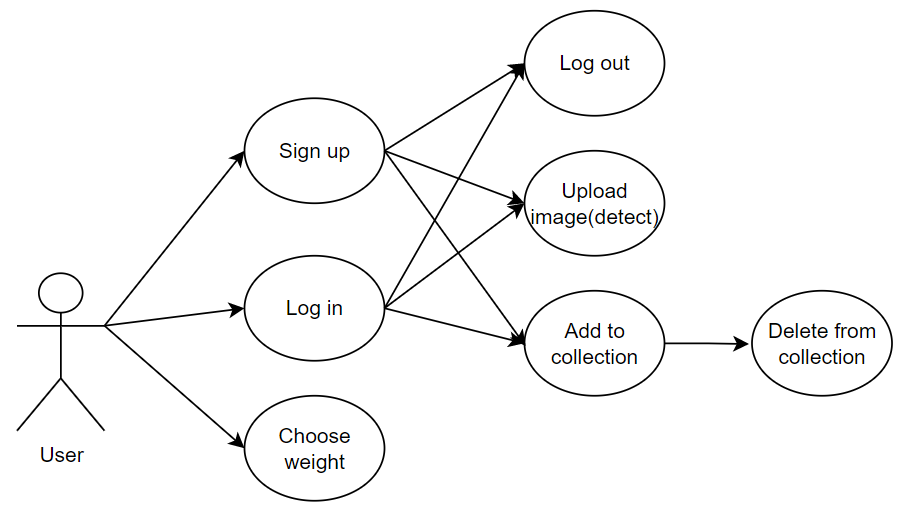
**Figure 2.1** Txxxxxxxxxx

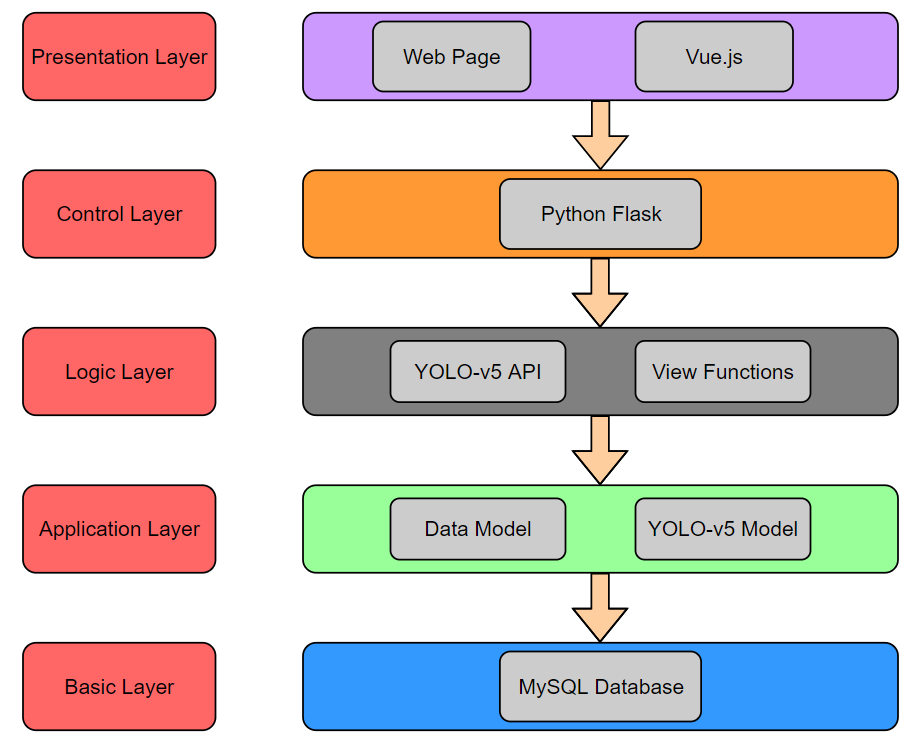
Therefore, CIoU-loss is used to calculate the central point distance between ground truth and prediction. In the basis of YOLO-v3, YOLO-v4 furthur enhance the network structure in the neck, by adding SPP module, allows the multi-scale intergration for pooling, and PAN structure to conact adjacent feature layers for prediction. Besides, YOLO-v4 also put more efforts in refining the inputs by using Mosaic, which could largely enhance data richness, leads to better network robustness.

Finally, YOLO-v5 was released in 2020. Compare to earlier version, YOLO-v5 adopts adaptive anchor, which allows anchor box could learn with the network, so previously predefined fixed (x,y,w,h) value will change by the learning process to compare with ground truth boxes, then update network parameters to obtain better training results. Therefore, the loss function also changed into GIoU loss. YOLO-v5 also adopts Focus module in backbone, which slice the data into 4 groups then concat them with channel, executing down-sampling procedure without largely losing information. The most interesting part of YOLO-v5 is that there are four options of pre-trained weights for choosing: s (small),m (medium),l (large),x (extra-large). The larger the weight is, the higher precsion goes, while the processing time also increase. These four weights are the results of different parameters in network depth, width, and different number of res unit when training, which results in different numbers of convolutional kernel in each layer. At last, YOLO-v5 also use adaptive image rescale module to improve detection speed.

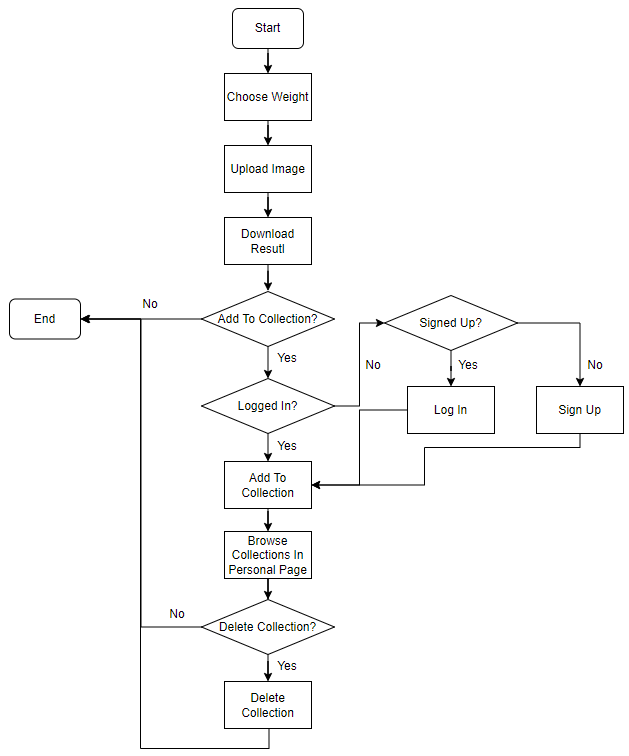








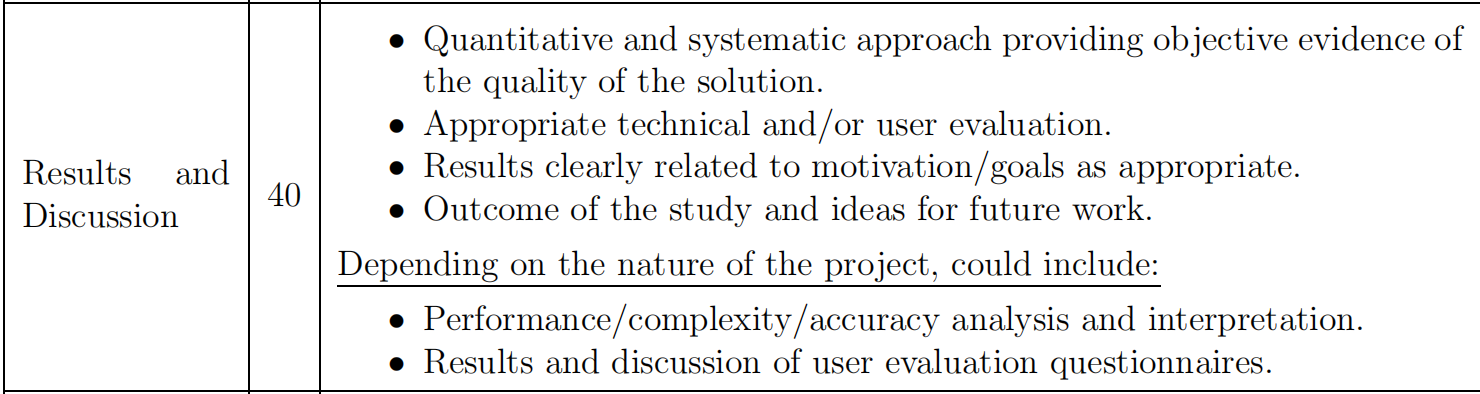
Structure Diagram



Flow Diagram

# Chapter 3 Results

<Results, evaluation (including user evaluation) *etc*. should be described in one or more chapters. See the `Results and Discussion' criterion in the mark scheme for the sorts of material that may be included here.>



Quantitative and systematic approach (mAP...)

Techinical /user evaluation ???

Outcome of the study and ideas for future work

Performance/complexity/ accurarcy analysis and inerpretation

Results and discussion of user evaluatin questionnaires ??? to be determined

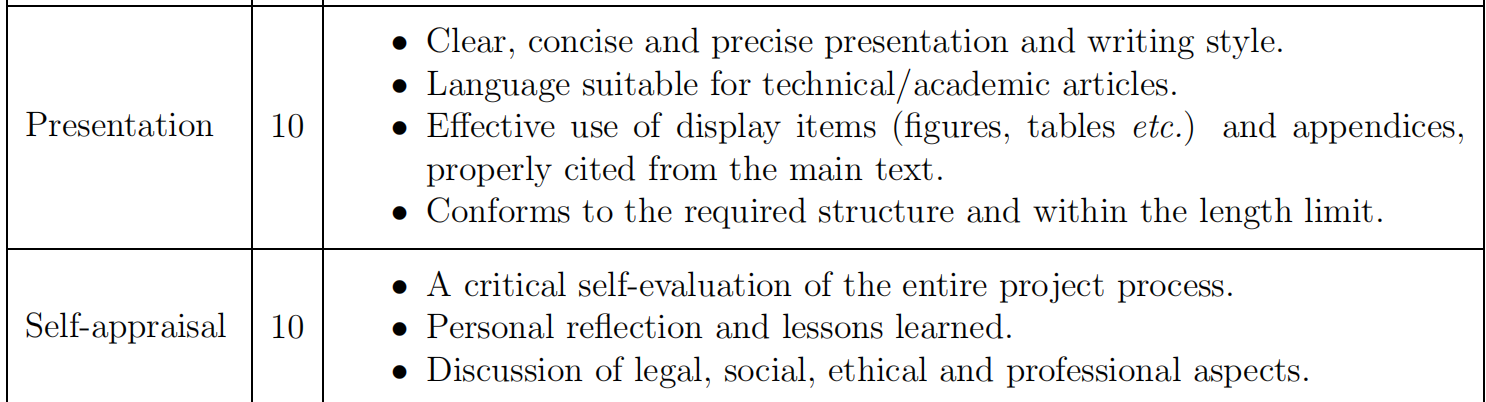
|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **YOLO-V5** | **Small** | **Meidum** | **Large** | **Extra Large** |
| **mAP(0.5)** | 0.2831 | 0.7147 | 0.7470 | 0.4277 |
| **Cls\_loss** | 0.0274 | 0.0068 | 0.0052 | 0.0195 |
| **Box\_loss** | 0.0500 | 0.0255 | 0.0225 | 0.0402 |
| **Train(epoch)** | 150 | 100 | 120 | 120 |
| **Speed(ms)** | 0.33 | 0.46 | 0.59 | 0.69 |

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# Chapter 4 Discussion

<Everything that comes under the `Results and Discussion' criterion in the mark scheme that has not been addressed in an earlier chapter should be included in this final chapter. The following section headings are suggestions only.>



## 4.1 Conclusions

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## 4.2 Ideas for future work

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# List of References

*<It is expected that the list would reflect the breadth and depth of scholarly research undertaken by the student during the course of the project.>*

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# Appendix A Self-appraisal

<This appendix must contain everything covered under the ’self-appraisal’ criterion in the mark scheme. Although there is no length limit for this section, 2-4 pages will normally be suﬃcient. The format of this section is not prescribed, but you may like to consider the following sections and subsections.>

## A.1 Critical self-evaluation

## A.2 Personal reﬂection and lessons learned

## A.3 Legal, social, ethical and professional issues

<Refer to each of these issues in turn. If one or more is not relevant to your project, you should still explain *why* you think it was not relevant.>

### A.3.1 Legal issues

<Discussion of legal issues>

### A.3.2 Social issues

### <Discussion of social issues>

### A.3.3 Ethical issues

### <Discussion of ethical issues>

### A.3.4 Professional issues

<Discussion of professional Issues>

# Appendix B External Materials

<This appendix should provide a brief record of materials used in the solution that are not the student's own work. Such materials might be pieces of codes made available from a research group/company or from the internet, datasets prepared by external users or any preliminary materials/drafts/notes provided by a supervisor. It should be clear what was used as ready-made components and what was developed as part of the project. This appendix should be included even if no external materials were used, in which case a statement to that effect is all that is required.>

Code: Yolov5 developed as part of the project

Dataset: VOC2007 ready-made components